KNOWLEDGE MANAGEMENT DETERMINANTS OF BREAKTHROUGH RESEARCH PRODUCTIVITY



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ABSTRACT

Recent technological advancements have brought about a wave of drastic change in the global supply and demand of knowledge and subsequently, in the generation of innovation. However, it has been argued that some industries and academic fields do not sufficiently take advantage of new opportunities afforded by the widespread, free and open availability of knowledge. Terms such as the Death of Innovation, Innovation Failure and Academic Failure have been used to describe the market failure of industrial Research and Development (R&D) and certain forms of academic research to sufficiently leverage these new opportunities, particularly with regard to societal problem-solving. An extensive and rapidly growing body of literature pertaining to new modes of knowledge productivity, such as open innovation, crowdsourcing and crowdfunding, through the use of the Internet, has demonstrated evidence that certain new technologies and methodologies may indeed offer significant economies of scope and scale in innovative problem solving. However, misaligned incentives may in some cases prevent the efficient leveraging of these new modes of productivity. These effects may be particularly pronounced in the academic context, which has long been criticised for its strict adherence to tradition and paradigmatic convergence. Despite this body of literature, there is a lack of knowledge as to the extent that academic researchers do indeed take advantage of these new modes of productivity, and furthermore, the extent to which their adoption influences research productivity. Thus, this research seeks to investigate the relationship between a behavioral orientation called 'technological propensity', or the extent to which individuals seize opportunities that offer significant economies of scale (such as crowdsourcing) and productivity. This research is undertaken at the individual level of analysis, which necessitates corresponding measurements of proximal, human-resources management determinants which may impact this relationship. These include personality, motivational values, work climate perceptions and human capital investments. Three studies are conducted to ascertain the extent of the relationships between these variables, and to provide a holistic perspective of the relationships between variables. First, a qualitative study, which samples award-winning scientists, academics researchers and innovators from across the world was conducted to develop theory. Amongst these are 3 Nobel Prize winners, 3 Lasker Award winners and 1 Fields Medal winner, among others. Second, a quantitative study, which sampled South African academic researchers, was conducted to test theory. Third and finally, a second quantitative study, which sampled 'crowd-workers', or users of an Internet-based crowdsourcing platform known as Amazon's Mechanical Turk, was conducted to provide

further insights into the relationships under study, in the open knowledge space (i.e. over the Internet). Qualitative data is analysed inductively, using thematic content analysis. Quantitative data is analysed through a series of statistical analyses, including multiple regression, mediation and moderation analyses. The findings of these studies suggest that the relationship between technological propensity and productivity is context-dependent and may only be suitable as a complementary methodology to certain forms of academic research, which is especially constrained by outside influences. Certain new modes of productivity may indeed enhance the rate at which 'breakthrough', or radically innovative research outputs are generated. The findings also suggest that differences in certain values-configurations and human capital investments may significantly impact this relationship. Based on the research findings, recommendations are made to improve research productivity in these contexts and recommendations for practice and for further research are made.

DECLARATION

I hereby declare this research report is my own, unaided work. It is being submitted in fulfillment of the requirements for the degree Doctor of Philosophy in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree of examination in any other university.

Asaf Rubin

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Signed on this the 7th day of September, 2018

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LIST OF ACRONYMS

5G	A Five-Generation Model of Innovation
6G	A Six-Generation Model of Innovation
BRP	Breakthrough Research Productivity
CWP	Crowd-Worker Productivity
HCI	Human Capital Investments
HIT	Human Intelligence Task
OCM	Organisational Climate Model
PI	Probabilistic Innovation
PVQ	Portrait Values Questionnaire
R&D	Research and Development
TIPI	Ten-Item Personality Inventory

ALPHA INDEX TABLE

Amazon's Mechanical Turk (MTurk)

A crowdsourcing Internet marketplace which enables individuals and businesses to coordinate the use of human intelligence to perform tasks that computers are currently unable to do. Users (called 'MTurkers') complete Human Intelligence Tasks (HITs) in exchange for monetary compensation. Examples include identifying images, transcribing documents or completing questionnaires.

Award-winning Scientists

Scientists, academic researchers and innovators from across the world, who have been awarded a major scientific award for their achievements. Examples include the Nobel Prize, the Fields Medal, the Wolf Prize and the Lasker Award.

Breakthrough Research Productivity

A state of research productivity, defined by having produced, or contributed toward a significant, radically-innovative research output.

Crowdsourcing

A sourcing model in which individuals or organisations use contributions from Internet users to obtain needed services or ideas. Crowdsourcing "represents the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call. (Howe, 2006:1). Crowdfunding is a type of crowdsourcing, which relates the sourcing of financial resources through online crowds.

Crowd-Worker Productivity (CWP)

A measure of performance or productivity of MTurk crowd-workers, measured by aggregate totals of MTurk HIT's (Human Intelligence Tasks), or MTurk projects over the number of years of experience as an MTurk crowd-worker. CWP is used in this study as an indication of individual-level output for crowd-workers.

Human Capital Investment (HCI)

A measurement of individual level intangible investments in the form education, training and experience. According to human capital theory (Becker 1962), investments in human capital may result in a return on investment over time, in the form of improved performance and productivity.

Work Climate Perceptions

Organisational climate is an intervening variable between the context of an organisation and the behaviour of its members; an indication of how employees experience their organisations. Work climate perceptions are therefore individual cognitive representations of the organisational setting "expressed in terms that reflect psychologically meaningful interpretations of the situation" (James, Hater, Gent & Bruni (1978: 783).

Motivational Values

A theory of values that incorporates biological, social and psychological motivational goals of individuals and relates these values to individual behaviour. Schwartz's (1992) values theory offers a theoretical structure of relative values.

Open Innovation

The use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation, respectively (Chesbrough, 2006:2).

Personality

"The set of psychological traits and mechanisms within the individual that are organised and relatively enduring and that influence his or her interactions with, and adaptations to, the intra-psychic, physical and social environments (Larsen & Buss, 2010: 4). These 'psychological traits' are often defined as a bundle of personality attributes. One of the most frequently used models of personality is as the Five Factor Model (or FFM) of personality (Costa & McRae, 1995), which is made up five personality attributes, including i) agreeableness, ii) extraversion, iii) neuroticism, iv) conscientiousness and v) openness to experience.

Probabilistic Innovation (PI)

A proposed as new management model of commercial R&D and academic research, that would theoretically be able to effectively reduce the time and cost dimensions of an R&D project. PI hinges on the 'probabilistic mechanism', or the way knowledge and information harness

probabilistic forces through the exposure of knowledge to large numbers of people or ‘nodes of creation’ to find solutions to problems

Research Productivity

A measure of performance or productivity of academic researchers, measured by aggregate totals of both locally accredited and internationally accredited journal article publications over a total number of years of academic research experience, and used in this study as an indication of individual-level output for academic researchers.

Sixth Generation Innovation (6G)

A proposed new paradigm of innovation, finance and knowledge management, which makes use of a probabilistic mechanism to exploit distributed knowledge systems to foster exponential knowledge creation and innovation. Examples of 6G mechanisms include open innovation, crowdsourcing and crowdfunding.

South African Universities

Defined as any university or institution of higher learning located within the borders of the Republic of South Africa and that employs academic researchers.

Technological Propensity

A measurement of behavioural orientation related to the extent to which individuals seize new technological opportunities that offer economies of scale to enhance their own productivity.

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

This chapter provides an overview of the structure of this study. A brief background pertaining to the theoretical tenets that form the foundation of the research are introduced and discussed. Thereafter, the significance of this study in its context is explored, as are the aims and objectives. The research questions and hypotheses are then introduced, as well as the theoretical model containing the variable relationships under study. A brief outline of all subsequent chapters is also provided.

1.2 BACKGROUND TO THE STUDY

> In terms of the Internet, it's like humanity acquiring a collective nervous system. Whereas previously we were more like a collection of cells that communicated by diffusion. With the advent of the Internet, it was suddenly like we got a nervous system. It's a hugely impactful thing" (*Wired,* Interview with Elon Musk 2012, p. 1).

The emergence of certain new recent technological advances has triggered drastic shifts in the global supply of knowledge (Tapscott & Williams, 2006). As a result, significant new opportunities to innovate have arisen (Ries 2011). However, it has been argued that certain industries and academic fields have not yet taken advantage of these opportunities (Alvesson & Sandberg, 2013; McKenna, 2014). Some have noted that despite widespread availability of knowledge, and the emergence of new tools that enable real-time communication and collaboration, returns to investment in research and development (R&D) have, paradoxically, declined over time (Cowen, 2011; Scannell, Blanckley, Boldon and Warrington, 2012). Terms such as the 'Death of Innovation' (Gordon, 2012), 'Innovation Failure' (Martin & Scott, 2000; Phan, Siegel & Wright, 2016) and 'Academic Failure' (Anderson, de Dreu, Nijstadt, 2002) have been used to refer to the failure of industrial R&D and academic research to leverage the significant scale economies associated with certain new technological and methodological advances.

This research seeks to investigate the relationships around the individual-level willingness to adopt certain new modes of productivity and research productivity in the academic research context. This research also seeks to investigate the potential of certain new modes of productivity to improve 'breakthrough' academic research productivity. In this context,

breakthrough research productivity is defined as research outputs that are radically innovative or that contribute radically new knowledge or understanding. The investigation of commercial R&D is beyond the scope of this research. Despite their differences however, academic research and commercial R&D do share certain similarities in that they both rely on knowledge as a key input in the innovation process. Furthermore, process changes in commercial R&D are often mirrored in academic research (Freeman, 1995; Castaldi & Dosi, 2010). Given their commonalities, literature related to commercial R&D is also reviewed.

The advent of the Internet, in particular, has drastically changed the landscape of knowledge economics (Howe, 2006; Brabham, 2008), or the supply and demand, distribution and access to knowledge, as an economic resource (Tapscott & Williams, 2006). As of January 2018, approximately 50% of the world's population (roughly 4 billion people) are connected to the Internet (Li, 2018). Attempts are underway to have the entire global population connected to the Internet by 2020 (Covington & Carskadden, 2013; Thompson, 2014). For Drucker (1994, p. 12), "the basic economic resource – the means of production – is no longer capital, nor natural resources, nor labour. It is and will be knowledge." Whereas previously, knowledge, as a resource, was scarce and concentrated (Hayek, 1945; Polanyi, 1963; Nonaka, 1994), it is now freely available, easily accessible and widely dispersed (Surowiecki, 2004; Howe, 2006; Tapscott & Williams, 2006; Brabham, 2008; Brabham, 2013). Previously, the problem of knowledge aggregation, or the difficulty in accessing tacit knowledge sources to solve problems, represented a barrier to innovation (Grant, 1996; von Krogh, Ichijo & Nonaka, 2000; Wang & Wang, 2012). Now, with the advent of the Internet, the problem of knowledge aggregation has essentially become void (Suh, Chi, Kittur & Pendleton, 2008; von Krogh, 2012; Nonaka & Toyama, 2015). Whereas previously global communications were limited and intermittent (Rogers, 1986; Hauser, 1996; Boyd & Ellison, 2007; Martin, 2017), they now occur instantaneously, and at a rate never before considered possible (Kock, 2004; Weber, Fulk & Monge, 2016; Martin, 2017). Whereas previously ground-breaking radical innovations occurred infrequently (Christensen, 1997; Koberg, Detienne & Heppard, 2003; Norman & Verganti, 2014; Christensen, Raynor & McDonald 2015), they now occur regularly, sometimes in the space of weeks (Kline & Rosenberg, 2010; Christensen, Raynor & McDonald, 2015; Slayton & Spinardi, 2016). These changes have impacted every facet of modern human life, with far-reaching global political, economic and social consequences (Perez, 2010; Alexander & van Knippenberg, 2014; Coccia; 2016).

Despite their widespread adoption and significant subsequent successes, some of these new modes of productivity seem not to have yet penetrated the echelons of academic, or scholarly research. In the context of this research, academic (or scholarly) research is differentiated from industrial, or commercial, 'private' R&D, in that it is not tethered to the need to generate profit. Furthermore, unlike private R&D, which is typically pursued for the purpose of improving organisational performance (Griffin & Hauser, 1996; Becker, 2015; Choi & Lee, 2017), academic research has frequently been associated with a moral responsibility to societal stakeholders (Fenton, Chillag & Michael, 2015) and to produce research that addresses important social needs (Jaffe, 1989; Radder, 2010).

It is argued that certain new technological advances associated with modern Information and Communication Technology (ICT), particularly the Internet may offer the means to fulfil these social obligations. There are numerous examples of Internet-based tools and methodologies that can enable knowledge aggregation at an unprecedented scale. Social networks such as Facebook and Twitter boast billions of active users (van Noorden, 2014), interacting and sharing knowledge in real-time (Kietzmann, Hermkens, McCarthy & Silvestre, 2011). Amazon, amongst legions of imitators (Arnett, Goldfinch & Chinta, 2018), has become a global online marketplace, not only for the trade of products, but for services and labour as well (Heizer, 2016). In 2017, an estimated 12.78 million transactions were carried out over Amazon, over a two-day period (Pandolph, 2017). Google, the world's premier and largest search engine optimises search results based on simultaneous input from over 40 000 searches per second (Afuah & Tucci, 2012; Halavais, 2017). Twitter feeds and Google Trends are monitored for real-time outbreaks of disease, and to optimise disaster management responses (Collier, Son & Nguyen, 2011). Amazon's Mechanical Turk platform has been used to crowdsource data collection for behavioural research (Brabham, 2013).

The Internet however is only a tool that has enabled these changes. Knowledge itself, particularly tacit knowledge, resides within individuals (Grant, 1996; Turner, 2018). Research in the phenomenon known as 'collective intelligence' has demonstrated that the cumulative problem-solving capability of large collectives of individuals far exceeds the capabilities of singular individuals, organisations and perhaps even entire economies (Wooley, Chabris, Pentland, Hashmi & Malone, 2010; Bernstein, Klein & Malone, 2012). Driven by the enhanced connectivity enabled by the Internet, new modes of productivity, such as open innovation (Chesbrough, 2003a), crowdsourcing (Howe, 2006) and crowdfunding (Brabham, 2008) have

emerged, and are increasingly adopted in a broad range of undertakings (Brabham, 2013). These new methods of knowledge aggregation function by leveraging the significant economies of scope and scale offered by large, diverse online collectives dispersed across the world (Malone, Lauchaber & Dellarocas, 2010). Through the Internet, online communities can be leveraged as 'innovation engines', which can solve problems at extremely low costs and in significantly reduced time frames (Woolley, Aggarwal & Malone, 2015). It is argued that this represents a significant opportunity for academic researchers seeking to enhance research productivity. More importantly, it is argued that these new modes of productivity may offer the means for academic researchers to address the needs of societal stakeholders by producing genuinely innovative research output cheaper and more efficiently, while maintaining scientific rigour.

For example, Wikipedia, a free, online and crowdsourced encyclopaedia has been described as has been described as "the most comprehensive, representative, and pervasive participatory platform for knowledge production ever created by humankind" (Adler, De Alfaro, Mola-Velasco, Rosso & West, 2011, p. 11). Despite validity concerns, studies have found that Wikipedia can maintain up to 99.7% accuracy, when compared to peer-reviewed journal articles (Kränenberg, et al., 2014). Every single article on Wikipedia is free and easily accessible to anyone with an Internet connection (Kaplan & Haenlein, 2010). Wikipedia and other similar online 'wikis' have come under considerable scrutiny, owing to their open-source accessibility (Holloway, Bozicevic & Borner, 2007; Kostakis, 2010; Christensen, 2015). Chief amongst these are concerns related to factual reliability of content (Niederer & van Dijck, 2010), systemic biases (Reagle & Rhue, 2011) and editorial vandalism (Heindorf, Potthast, Stein & Engels, 2015). For Black (2010: 1), the content of most Wikipedia articles can be described as "truth, half-truth and some falsehoods". Wikipedia does however acknowledge these faults and accedes that information on Wikipedia should not be used as a primary source for research, either academic or informal (Solorzano, 2013). Nevertheless, the high level of accuracy attained in certain areas may provide indication as to usefulness of large online collectives, under certain conditions.

Another example of the success of collective intelligence is that of FoldIt, an online puzzle video game that invites users from around the world to fold virtual proteins cells from home (using personal computers), and thereby contribute to important medical research (Good & Su, 2011). Using this method, significant strides have been made in cancer, HIV-AIDS and

Alzheimer's disease research (Peckham, 2011; Christodoulou, 2012). In one noteworthy example, a group of non-expert volunteers were able to solve a problem that had expert scientists stumped for several years, in the space of three weeks (Peckham, 2011). InnoCentive is an online platform that provides a marketplace for solution seekers and problem solvers to interact (Brabham, 2008). Through 'commission-based research and development', InnoCentive allows organisations to pose 'challenge problems' for anyone to solve (Lakhani & Panetta, 2007). Notable InnoCentive successes include significant advances in cancer survival, and Amyotrophic Lateral Sclerosis (ALS) research (Lee, Kim & Hong, 2017). The Polymath Project is an online, collaborative project aimed at solving difficult mathematical problems by crowdsourcing solutions (Crenshaw & Kittur, 2011). The project has successfully crowdsourced several notable solutions to complex mathematical problems, drawing from both expert and amateur input (Nielsen, 2012). Crowdfunding is a process, or a mechanism of external financing which leverages small online contributions or payments to reach a monetary goal (Torr-Brown, 2013). In 2015, approximately US$ 34.4 billion was raised online through crowdfunding. This represents an approximate 200% increase from 2014, in which a total of US$16.2 billion (Salmann, 2016) was raised. The World Bank estimates that crowdfunding will surpass US $90 billion by 2020 (Barnett, 2015). In 2014, a crowdfunder launched a campaign to fund a "world-record breaking potato salad" (Siva, 2014, p. 384). What was initially intended as a hoax eventually raised over US$50,000 and worldwide media attention (Dey & Marti, 2016).

Some schools of thought however, view the leveraging of collective intelligence, 'open source' innovation and its related mechanisms such as crowdsourcing and crowdfunding in a less positive light. Trott and Hartmann (2009), for example respond to Chesbrough (2003a; 2006), arguing that the distinction between open and closed models of innovation represents a false dichotomy. Van de Vrande, de Jong and Vanhaverbeke (2009) cite literature on barriers to innovation, including 'Not-Invented Here' (NIH) syndrome, which may be a detriment to the implementation of open innovation practice. Indeed, the use of crowdsourcing and crowdfunding have raised a number of moral concerns, relating to false input (Rosenzewig, 2006; Brabham, 2012), and taking unfair advantage of unpaid labourers (Fieseler, Bucher & Hoffman, 2017). The moral implications of crowdsourced reviews, on popular platforms such as Yelp and TripAdvisor have also been condemned for their susceptibility to bias and 'groupthink' (Askay, 2013; Kuehn, 2017).

Despite these criticisms, the examples discussed above show the scope and potential of knowledge and fund dissemination and aggregation over the Internet; a potential way to overcome the problem of knowledge aggregation, maximally enhance research efficiencies, and produce radically innovative output (Brabham, 2008; Torr-Brown, 2013). Collectively, these new techniques, technologies and methodologies represent a new wave of technological, social and economic change, characterised by: i) a shift from static to fluid knowledge dynamics; ii) super-enhanced, unprecedented global connectivity; and iii) a resultant exponentially increasing probability of further technological and economic change and innovation. In contrast to previous waves of technological and economic change, which related to the production of steel and heavy engineering, or mass production and automobiles (Kondratieff, 1979; Smith, 2010), the present wave offers radically enhanced opportunities of scope and scale (Avital, 2011), where knowledge dissemination, aggregation and analysis occurs at an unprecedented rate. Indeed, the application of these new technological advances has resulted in unprecedented economic and social growth (Curran, Fenton & Freedman, 2016). A wave of industrial technological progress has ensued, by harnessing the power of the Internet, and the large collectives that inhabit it (Jin & Cho, 2015). In the interest of saving time and costs, organisations frequently turn to open-sourced R&D (Enkel, Gassmann & Chesbrough, 2009). Examples range from T-shirt design (Brabham, 2008) and facewash production (Sciaca, 2016) to raising venture capital for technology start-ups (Belleflamme, Lambert & Schwienbacher, 2014) or the completion of 'micro-tasks' that computers are unable to perform (Harris, 2011). Global high-tech leaders, such as Google, IBM and Microsoft have all introduced open innovation initiatives (Metz, 2015).

Given the abovementioned example, it is clear that some forms of private R&D have begun to take advantage of certain new modes of productivity, enabled by the Internet, and which ultimately contribute to organisational performance and profitability (Melville, Kramer & Gurbaxani, 2004). However, the extent to which academic researchers take advantage of these same opportunities, to fulfil their obligations to societal stakeholders, is unclear. Academic research has long been criticised for its' perceived rigidity and emphasis on tradition (Kuhn, 1962; Mort & Lakatos, 1970; De Rond & Miller, 2005; Camanario, 2009) and thus, its purported failure to produce knowledge that is useful for solving practical problems. Academic research has been repeatedly accused of being myopic (Bartunek & Rynes, 2014; Walther, 2002), inflexible (Spencer, 2001), routinised (Anderson, de Dreu & Nijstad, 2002) and overly

reliant on traditional paradigms of thought (Campanario, 2009; Bornmann, Leydesdorff, & Van den Besselaar, 2010).

The 'Death of Innovation' hypothesis purports that returns to R&D investments typically decrease over time (Gordon, 2012), evidenced by a decreasing trend in the rate of growth of patent statistics (Kortum, 1997; Gordon, 2012). Thus, technological breakthroughs tend to become harder to achieve over time (Kortum, 1997). In certain industries, this has resulted in a notable decrease of innovative output over time. For example, Scannell, et al. (2012, p. 912) find that despite significant scientific and technological advances, returns to investment in pharmaceutical R&D have "declined fairly steadily". Furthermore, it has been argued that the pursuit of innovative solutions, or the development of unprofitable drugs is outside the ambit of pharmaceutical R&D, which is characteristically bound by organisational profitability (Martin & Scott; McKenna, 2014). Pharmaceutical firms may benefit more from closed models of innovation which prioritise customer retention, rather than innovative, or 'once-off' solutions (Chesbrough, 2003a; Gassman, Enkel & Chesbrough, 2010; Bianchi, Cavaliere, Chiaroni, Frattini, Chiesa, 2011). In other words, pharmaceutical innovation may be constrained by a misalignment of incentives (Martin & Scott, 2000; McKenna, 2014).

Similar arguments have been raised in the context of academic research. The term 'academic failure' has been used to describe the market failure of academic research to innovate, and create new knowledge (Dewald, Thursby & Anderson 1986; Campanario, 2009), specifically that that addresses the needs of societal stakeholders (Fenton, Chillag & Michael, 2015). It has been argued that shared academic values tend to converge on paradigms which may constrain the academic process (Kuhn, 1962; Lakatos, 1970). Frickel & Gross (2005) suggest that certain academic fields emerge in response to institutional pressure to 'normalise' to widely accepted paradigms of thought, and subsequent perceived academic legitimacy amongst peers. For Amabile (1997), organisational innovation is a function of openness and creativity. Thus, normalisation, or 'routinisation' in the academic process may constrain openness, creativity and innovation (Anderson, de Dreu & Nijstad, 2002), rather than stimulating it. Consequently, academic routinisation may represent a cost to stakeholders, as academic fields become less innovative in the pursuit of legitimacy and normalisation (Frickel & Gross, 2005). Like the case of the pharmaceutical industry, academic innovation may be constrained by a misalignment of incentives. Indeed, a number of studies have found that academic research may be rejected on account of its innovativeness, or non-conformity (Campanario and Acedo,

2007, Campanario, 2009). Cultural convergence towards 'publish or perish' (Richard, Plimmer, Fam & Campbell, 2015), an increasingly inflexible peer-review structure (Bornman, et al., 2010), and a plethora of "adding to the literature contributions" (Alvesson & Sandberg, 2013, p. 128) seem to have contributed to this trend. As a result, the publication of genuinely innovative research, in certain academic fields, may be constrained, and obligations to societal stakeholders may not be sufficiently met.

Thus, a fundamental theoretical tension emerges. On one hand, the emergence of new forms of ICT, particularly the Internet, have enabled mass communication and collaboration, and new modes of productivity which offer a potential solution to the problem of knowledge aggregation. In this context, important contributions to important social needs (for example advancements in cancer research or the aggregation of entrepreneurial venture capital) can be made in significantly reduced time frames and at significantly reduced costs. On the other hand, it seems that that some forms academic research may have not yet taken advantage of these new opportunities, evidenced by a range of criticisms, including routinisation, non-innovativeness and a failure to sufficiently address the needs of societal stakeholders. This research seeks to explore this fundamental tension, by investigating the extent to which certain new modes of productivity (such as open innovation, crowdsourcing and crowdfunding) have been, or might be adopted in the academic research context, and their relation to academic research productivity. The significance of this research is now discussed.

1.3 SIGNIFICANCE OF THE STUDY

This research seeks to make a modest, yet important contribution to the innovation and knowledge management literature. Schumpeter's (1942, p. 84) seminal theory of 'creative destruction' predicts a "process of industrial mutation, that incessantly revolutionises the economic structure from within, incessantly destroying the old one, incessantly creating a new one". Foster's (1986) seminal notion of technology S-Curves predicts that certain technologies (or products and processes) become outmoded over time, and are summarily replaced with newer, more suitable technologies. Similarly, Nielsen (2012) suggests that significant changes in the scientific research landscape occur at points where the discovery process itself changes dramatically. Thus, the advent of drastic, Schumpeterian methodological change may prompt equally drastic change in returns to investment in research and R&D. It is argued therefore that change is required to address the problems associated with the routinisation of academic

research. It is further argued that some forms of academic research are nearing or have already reached the limit of their methodological S-Curve. Certain new technological and methodological advances therefore, such as the Internet, open innovation, crowdsourcing and crowdfunding may collectively represent a new methodological S-Curve. Following Nielsen (2012), the adoption of this new methodological S-Curve may instigate drastic changes in returns to investment in research and R&D. Given their association with significant economies of scale and scope, it is argued that the adoption of these new modes of productivity may represent the means to overcome the constraints of routinisation in academic research, and thereby increase the rate at which academic innovation occurs. Consequently, the moral obligation of academic researchers to societal stakeholders may be more efficiently met.

Rothwell (1994) provides a useful overview of the history of industrial innovation by categorising certain phases of industrial innovation into 'generations' ranging from a First Generation (1G) to a Fifth Generation (5G). Each successive generation is differentiated from the previous in that the U-Curve associated with development time and costs of production decreases. Thus, 1G represents a U-Curve furthest from the origin, while 5G represents a curve that is closest to the origin. Although the 5G model relates primarily to industrial innovation, the progression of industrial innovation and innovation in academic research may share many commonalities (Mansfield, 1991; Mansfield, 1998). The study of technology transfer (from academic to commercial contexts) has provided examples of similar progressions (Etzkowitz & Leydesdorff, 2000; Debackere & Veugelers, 2005). Freeman (1995, p. 5), argues that "national and regional systems of innovation remain an essential domain of economic analysis." In other words, trends in innovation tend to progress in parallel, so long as they are contained within similar economic domains. Thus, while the 5G model relates primarily to industrial innovation, it may offer useful applications in the investigation of academic research. Indeed, Christensen, Johnson and Horn (2010) suggest that the emergence of certain new technologies have radically altered the way in which universities function and that further radical change is inevitable. Christensen, and Eyring (2011) argue that increases in access in to new technologies in the academic context have effectively increased the likelihood of competitive disruption.

Indeed, Callaghan (2017a) builds on Rothwell's (1994) 5G model, suggesting that a new Sixth Generation of innovation (6G), which relates to the use of new significantly scalable technologies and methodologies such as crowdsourcing, has already emerged, and its

applications may range from industrial R&D to academic research. Furthermore, Callaghan (2015a; p. 67) argues that the application of "crowdsourced R&D" to the research process itself could result in exponentially improved R&D productivity, as a research methodology that takes advantage of certain new technological opportunities.

Building on these streams of literature, it is argued that 6G may represent a new iteration of creative destruction (Schumpeter, 1942), a new methodological S-Curve (Foster, 1986), and a drastic change in the discovery process itself, which according to Nielsen (2012), may instigate equally drastic change in returns to investment in research and R&D.

In the context of this research, the term 'technological propensity' is used to refer to the extent to which academic researchers do indeed take advantage of new scalable technological and methodological opportunities. Technological propensity is therefore a behavioural orientation, which might range from low to high. Thus, this research seeks to investigate the relationship between technological propensity and academic research productivity. Given the examples discussed above, it would be expected that academic researchers with high technological propensity may produce more research output, while those with low technological propensity may produce less.

Academic research productivity however may not necessarily be indicative of innovativeness, or an ability to meet the needs of societal stakeholders. For this reason, this research also seeks to investigate the determinants of 'breakthrough' academic research productivity, or academic research that is genuinely, radically innovative and therefore which may indeed sufficiently meet the needs of societal stakeholders. This research also seeks to explore the relationship between technological propensity and productivity outside of the context of academic research, to provide insight into the workings of the '6G space', where large, online collectives are harnessed for their processing power.

This research comprises of three interlinking studies, including two quantitative studies and one qualitative study. In this research, qualitative and quantitative data collection and analysis was conducted concurrently, or roughly at the same time (Creswell, 2003). For Takashori and Teddlie (2010), the overlaps between the three different studies represents a point where integration can occur at the data collection, data analysis and interpretation stages.

The rationale for incorporating these three different studies is to provide comprehensive trans-contextual and multi-dimensional investigation of the relationships in question. The quantitative studies are conducted to investigate the relationships around technological propensity and productivity in different contexts (namely, the academic research context and the '6G' space). The qualitative study is conducted to investigate qualitative drivers of Breakthrough Research Productivity. More specifically, Study 1 seeks to assess the relationship between technological propensity and productivity in the academic research context. Study 2 seeks to investigate the determinants of breakthrough research productivity (BRP) in the context of academic research. Study 3 seeks to investigate the relationship between technological propensity and productivity, in the '6G space'. It is hoped that this three-dimensional approach will provide a useful, holistic synthesis of the relationships under investigation. The minutiae of these three studies are discussed in further detail in subsequent chapters.

It is argued that this research is important for the following reasons. Firstly, in a context where returns to investment in research and R&D may be constrained (Anderson, de Dreu & Nijstadt, 2002; Nielsen, 2012) and has typically avoided competitive disruption (Christensen, & Eyring, 2011), this research seeks to offer a novel perspective on possible new modes of productivity which could potentially increase the rate at which academic research output is produced (Brabham, 2008; Torr-Brown, 2013). By leveraging the scale advantages associated with these new modes of productivity, it may be possible to exponentially enhance returns to investment in academic research (Avital, 2011; Woolley, Aggarwal & Malone, 2015). Therefore, this research seeks to make an important contribution to the theory surrounding academic research productivity.

Secondly, as previously noted, quantitative measures of academic research productivity may not be indicative of the inherent innovativeness of academic research output (Anderson, de Dreu & Nijstad, 2002; Camanario, 2009; Alvesson & Sandberg, 2013). Often, academic researchers may seek to produce academic research output which is inherently 'safe', in that its content may conform to traditional, 'routinised' paradigms associated with its field, in the interest of legitimacy and normalisation (Kuhn, 1970; Kortum, 1997; Gordon, 2012). However, the adoption and application of certain new modes of productivity, such as crowdsourcing, have been shown to produce significantly improved problem-solving capabilities (Surowiecki, 2004; Nielsen, 2012), and innovative potential (Howe, 2006; Brabham, 2013), by drawing on

the collective intelligence of large, diverse, geographically dispersed, online crowds of individuals (Woolley, et al, 2010; Malone, Lauchaber & Dellarocas, 2010). Given the numerous examples of success in the context of industrial R&D (e.g. InnoCentive, FoldIt and the Polymath Project), it is argued that the adoption and application of these processes to the academic research process may not only exponentially increase academic research output but may also exponentially increase the inherent innovativeness of academic research output. Therefore, this research also seeks to make an important contribution to theory surrounding academic innovation.

Thirdly and finally, given the moral issues associated with academic research that does not sufficiently address the needs of societal stakeholders, the development and testing of theory regarding the use of new scalable research methodologies may provide important insight into the potentialities of innovative academic research that addresses the needs of societal stakeholders. The example of the Polymath Project demonstrates that even extremely complex problems can be solved by harnessing the power of large online collectives. The example of FoldIt demonstrates that innovative solutions to serious societal problems (i.e. cancer research) can be achieved in significantly reduced timeframes and at a significantly reduced cost. Thus, it is argued that this research is critical, in a global context where academic research has been accused of becoming increasingly routinised (Anderson, de Dreu & Nijstad, 2002) and of insufficiently addressing the needs of societal stakeholders (Fenton, Chillag & Michael, 2015).

In summary, this research seeks to contribute novel perspectives on i) the productivity of academic researchers, ii) the innovative (or 'breakthrough') productivity of academic researchers and iii) the extent to which innovative academic research might sufficiently address the needs of societal stakeholders. These contributions are made by investigating the relationship between technological propensity and productivity, across three different contexts. Given that this research is conducted at the individual level of analysis, it is also important to take into consideration certain individual-level differentiating characteristics, which may, in some cases impact the relationships under investigation. These are now discussed.

1.4 THEORETICAL MODEL

This research is conceived through the lens of management theory, which may offer a useful multidisciplinary perspective of the phenomena under study (Smith, 2010). More specifically, this research is conceived at the nexus of three interlinking sub-disciplines of management, including knowledge management, innovation management and human resources (HR) management. Knowledge management is typically concerned with the efficient use of knowledge to achieve objectives (Nonaka, 1994). Innovation management is primarily related to the management of the subsequent outcomes of knowledge management (Crossan & Apaydin, 2010). HR management is primarily concerned with the management of people, to improve performance, in line with objectives (Collings & Wood, 2009). This study is also associated with Research and Development (R&D) management, or the study of R&D processes and the transfer of knowledge and innovation (Chiesa, 2001). It is hoped that this multi-pronged approach to management theory will produce a holistic and multi-contextual overview of the phenomena under study.

As discussed, this research is focused on the individual level of analysis. To assess the relationship between technological propensity and productivity, at the individual level, individual-level differentiations must also be considered. The study of innovation at the individual level often involves examination of knowledge, skills, abilities and other factors (KSOAs) that lead to innovative behaviour (Becker, 1994). King and Anderson (2002) list four facilitators of innovative performance. These include i) personality, ii) motivation, iii) job characteristics, and (iv) cognitive ability. This research loosely builds on King and Anderson's (2002) theoretical framework. An examination of cognitive ability is beyond the scope of this research. Instead, human capital investments (HCI), which include intangible investments in human capital such as education, training and experience, are considered as a potential facilitator of innovative performance. Each of these is introduced and briefly discussed below. First, a consideration of technological propensity follows.

1.4.1. Technological Propensity

As previously discussed, the term technological propensity is used in this research to refer to the extent to which individuals take advantage of new technological and methodological opportunities which may offer substantial economies of scale in the research process and in

certain other forms of productivity, such as open innovation, crowdsourcing and crowdfunding. Technological propensity is therefore a behavioural orientation, which may be associated with openness, risk-taking propensity, tolerance for disruption and the propensity to collaborate. Previous studies have found a positive association between collaboration and academic productivity (Laband & Tollison, 2000; Dietz & Bozeman, 2005; Ductor, 2015). However, the extent to which the adoption of these and other technological advances impacts innovative productivity is unclear, since increases in research productivity may not necessarily lead to increases in innovativeness. Thus, technological propensity also comprises measurements of creativity and innovativeness. Numerous previous studies have found positive associations between individual-level creativity, innovation and productivity (Scott & Bruce, 1994; West & Altink, 1996; Edwards, 1998; Yi, Fielder & Park, 2006; Liu & Phillips, 2011), although these are typically dependent on a number of contextual factors (Gatgnon, Tushman, Smith & Anderson, 2002; King & Anderson, 2002; Anderson, Potocnik & Zhou, 2014). Given these examples, it would be expected that technological propensity, as defined here, may be positively associated with productivity. This research seeks to build on these previous studies by investigating the relationship between technological propensity and productivity. In this way, this research seeks to address a gap in the literature, or the lack of knowledge relating to the extent to which individuals take advantage of certain new scalable modes of productivity (such as crowdsourcing) to improve research productivity. Examples of contextual factors which may impact the relationship between technological propensity and productivity include personality, motivation and job characteristics (such as work climate perception). The first of these, personality, is now discussed.

1.4.2 Personality

West (2002) cites the importance of measuring differences in individual-level personality in assessing the relationship between innovativeness and productivity. For the purpose of this research, personality is measured using a Five Factor Model (FFM) of personality (Costa & McCrae, 1992), also known as the 'Big Five' model. Empirical research has shown that this model is able to account for different personality traits, without overlapping (Boyle, 2008). It has been argued that the FFM is limited in its capacity as a predictive mechanism (Costa & McCrae, 1995; McCrae, 2001). However, the FFM is one of the most widely used and comprehensive measure of personality used in social science research (Barrick, Mount & Judge, 2001). The FFM is comprised of five broad categories of personality including i)

neuroticism, ii) agreeableness, iii) conscientiousness, iv) openness to experience and v) extraversion. Costa and McCrae (1989) refer to the FFM as a hierarchical organisation of personality traits, applicable across observers and cultures. Previous studies have investigated the relationship between innovation and personality. Individuals that are open to experience and extraverted tend to be more creative, and therefore more innovative (Rushton, Chrisjohn & Fekken, 1981). Conversely, those that are neurotic tend to be less creative and innovative (Fesit, 1998). For Rogers (1995), individuals who are open to experience are more likely to be early adopters in the diffusion of innovation process. Such individuals are likely be risk takers, opinion leaders and social leaders and may therefore be highly likely to adopt new modes of productivity. Numerous studies have investigated the relationship between personality and work performance, or productivity. Academic research productivity (measured as journal article publications over time) has been found to be positively associated with conscientiousness (Feist, 1998; Rushton, Jackson & Paunonen, 1981) and openness to experience (Baer & Oldham, 2006; Edwards, 1998). Conversely, academic research productivity has also been shown to be negatively associated with agreeableness and neuroticism (Cubel, Nuevo-Chiquero, Sanchez-Pages & Vidal-Fernandez, 2016; Rushton et al., 1981). This research seeks to extend these previous studies by examining the relationship between personality and technological propensity, and by investigating the mediating effect of personality on the relationship between technological propensity and productivity. In this way, this research aims to address a gap in the literature as to whether personality influences the uptake of certain new modes of productivity. Motivational values are briefly introduced and discussed next.

1.4.3 Motivational values

Amar (2004) argues that motivational factors, both extrinsic and intrinsic, may impact the relationship between innovativeness and productivity. Schwartz (1992) offers a model of motivational values, which incorporates differing biological, social and psychological differences. In this context, motivational values are "desirable, trans-situational goals that vary in importance as guiding principles in people's lives," and can be differentiated according to the motivational goals that they express (Ross, Schwarz & Surkiss, 1999, p. 51). The Schwartz (1992) model of motivational values is characterised by a distinction of four higher-order motivational values, including i) self-transcendence, ii) openness to change, iii) conservation, and iv) self-enhancement. Previous studies have found that intrinsic rather than extrinsic

motivations tend to lead to innovative performance and productivity (Farris & Cordero, 2002; Grant, 2008; Gezelter, 2015). This research seeks to complement these previous studies by investigating the relationship between motivational values and technological propensity and by investigating the mediating effect of personality on the relationship between technological propensity and productivity. In this way, this research aims to address a gap in the literature as to whether certain motivational values influence the adoption of certain new modes of productivity. Work climate perceptions are briefly discussed next.

1.4.4 Work climate perceptions

Scott and Bruce (1994) suggest that work climate perception may be a determinant of innovative output. Patterson, West, Shackleton, Dawson, Lawthom Maitlis & Wallace (2005) introduce the Organisational Climate Model (OCM), a comprehensive a typology of organisational climate measures. According to the OCM, there exist four possible classifications of organisational climate. For the purpose of this study, only two of these models are investigated; i) the internal process model (IPM) and ii) open systems model (OSM), since these offer a given perspective on work climate perceptions. Previous studies have found that employees that perceive their work climates to be flexible, reflexive and outwardly focused (i.e. OSM) tend to be more innovative (Scott & Bruce, 1994; Amabile, 1998). Conversely, those that perceive their work climate to be traditional and formalised (i.e. OSM) tend to be less innovative (Adams, 2003, McLean, 2005). The relationship between work climate perception and productivity however, tends to vary according to context (Schneider, 2000; Patterson, et al., 2005). In the context of academic research, it has been found that work climates that promote collaboration often tend to produce higher levels of productivity (Lee & Bozeman, 2005). This research seeks to add to this body of literature by investigating the relationship between work climate perceptions and technological propensity. In this way, this research aims to address a gap in the literature as to whether certain work climate perceptions influence the adoption of certain new modes of productivity. Human Capital Investments are discussed next.

1.4.5 Human Capital Investments (HCI)

Human Capital Investments (HCI) refers to the accumulation of ‘productive knowledge’, in the form of education, training and experience, and is purported to be positively associated

with work productivity (Becker, 1962). Becker (1994, p. 11) offers a definition of HCI as "activities that influence future real income through the embedding of resources in people." Previous studies have found positive associations between HCI and productivity (Black & Lynch, 2001). Redding (1996) discovers a positive relationship between HCI and organisational R&D performance. Indeed, increased investments in human capital have been found to be associated with improved creativity and innovation (Black & Lynch, 2001; Garton & Makins, 2017). It is also recognised that individual differences, such as personality, motivation and work climate motivations may impact the relationship between HCI and productivity (Amabile, 1997; Sebert, Crant & Kramer, 1999; Heckman, 2000). This research seeks to contribute to this literature by investigating the relationships between human capital investments, technological propensity and productivity. In this way, this research aims to address a gap in the literature as to whether investments in human capital might influence the adoption of certain new modes of productivity. The background to the methodological approach is now discussed.

1.5 BACKGROUND TO THE METHODOLOGICAL APPROACH

This research seeks to offer a holistic perspective of the relationships between technological propensity and productivity. Thus, three different populations were sampled, and both qualitative and quantitative methods were used to gather and analyse data, and to make managerial recommendations based on research findings. In Study 1, a sample of 30 award-winning scientists, innovators and academic researchers were interviewed. This sample included winners of the Nobel Prize, the Fields Medal, the Wolf Prize and the Lasker Award, amongst others. In Study 2, questionnaires were distributed to a sample of 457 academic researchers from nine different South African universities. In Study 3, questionnaires were distributed through Amazon's Mechanical Turk (MTurk), an online crowdsourcing platform, to a sample of 569 crowd-workers.

A theoretical model of relationships between variables was constructed from literature (see Figure 1, below). Data collected from Studies 1, 2 and 3 were analysed, following methodological precedent. In Study 1, data gathered from qualitative respondents was analysed following the methods prescribed by Miles and Huberman (1994) and Thomas (2006). This involved an inductive approach, where raw data was condensed and summarised, findings were derived in relation to the research objectives and a framework of relationships was developed.

In Studies 2 and 3, data gathered from quantitative respondents was analysed statistically. These analyses involved a deductive approach, where data analyses were conducted "to test whether data are consistent with prior assumptions, theories or hypotheses identified or constructed by an investigator" (Strauss & Corbin, 1998, p. 12). In this case, "prior assumptions" refers to the theoretical model derived from the literature. The findings of Studies 1, 2 and 3 are subsequently compared and discussed, in relation to literature. Thereafter, conclusions are drawn and recommendations for practical managerial applications and for further research are made. The model of relationships tested quantitatively is depicted in Figure 1 (below), which represents a summary of the research problem, and in which certain theoretical associations introduced above are included. The research problem and research questions are now introduced and discussed.

1.6 RESEARCH PROBLEMS AND RESEARCH QUESTIONS

There exists a fundamental tension between the predictions of innovation theory (Rothwell, 1994; Nielsen, 2012) versus those predictions of the problem-solving capacity of academic research (Anderson, et al., 2002; Campanario, 2009). An investigation of the relationship between technological propensity and productivity may help to address this tension. It is argued that ignorance of the extent to which technological propensity is associated with productivity comes with a cost. Without knowledge of how academic research productivity can transcend the threshold of routinisation, improvements to certain academic research processes cannot be implemented and managed. Thus, the research problem addressed in this study is the lack of knowledge around the relationship between technological propensity and productivity, across three different contexts. It is argued that this study is the first to investigate this relationship, and therefore represents a critical contribution to the knowledge management and innovation management literature. It is argued that the absence of this research might represent an unnecessary cost borne by academic researchers and institutions. It may also represent an unnecessary cost to the societal stakeholders who may otherwise benefit from innovative academic research output. This knowledge, or a 'proof of concept' of whether technological propensity is indeed significantly associated with productivity, also offers a platform for further research to develop and test theory relating to the causes that underpin these relationships. The aim of the research, research objective, research questions and hypotheses are now introduced.

1.6.1 Aim of the research

Following Thompson (2014), research aims are the knowledge and understanding required to answer a research question. The primary aim of this research therefore, is to investigate the relationships around technological propensity and productivity, and to generate insight into how to accelerate breakthrough research productivity. This is taken to be of particular importance in the South African context, where improvements in breakthrough research productivity might help to address serious social problems.

1.6.2 Research objective

Following Thompson (2014), research objectives are specific research actions that define the research structure to fulfil the aims defined by the research question. The objective of this research therefore, is to develop and test theory that relates technological propensity to productivity, at the individual level of analysis, across three different contexts. The overarching objective of this research is to generate insight, and to provide recommendations for managerial practice that are tailored to enhance the efficiency and effectiveness of academic research. The research questions derived from this objective are now introduced.

1.6.3 Research questions and derived hypotheses

The theoretical rationale that underlies the research questions has been discussed above. Research questions and hypotheses are now introduced, in relation to the body of theory outlined above.

It has been argued that the academic research process, in some cases, tends to conform to paradigmatic standards which are fixed, standardised and routinised (Anderson, et al., 2002; Campanario, 2009; Bornman, et al., 2010; Alvesson & Sandberg, 2013). According to Callaghan (2014a), the application of certain new technologies, techniques and methodologies to the research (or R&D) process may help to overcome the problems associated knowledge aggregation and routinisation. These new technologies, techniques and methodologies are differentiated from others because they offer significant scale advantages, and their application may therefore enable significant boosts in productivity that is otherwise constrained. Indeed, the application of these ‘Sixth Generation’ techniques, technologies and methodologies have

demonstrated significant problem-solving success and productivity enhancements in some forms of medical research and disaster management, amongst other examples (Swan, 2012; Torr-Brown, 2013). Thus, it is argued that 'technological propensity', or the extent to which individuals seize opportunities that offer significant economies of scale, is positively related to productivity (or output over time). Research Question A is thus introduced:

RQA: What is the relationship between technological propensity and productivity?

Academic researcher productivity may be dependent on a number of different factors. Becker (1962) suggests that investments in human capital, such as education and training and the accumulation of experience are amongst the strongest predictors of work performance and productivity. Previous studies have also found that human capital investments (HCI) are positively associated with creativity and innovativeness (West, 2002). Thus, in the context of this research, academic researchers with more education, training and experience may produce more research output. However, as discussed, some academic research processes may be constrained by prevailing orthodoxy (i.e. routinisation) which may tend to disfavour creativity and innovativeness. In this case, investments in human capital may result in decreasing productivity, since individuals that produce creative or innovative research output may experience rejection (Campanario, 2009). There is also the possibility that HCI accumulated in the academic space might reflect the routinised nature of some academic processes (Bornman, et al., 2010). In this case, individuals who have accumulated HCI in the academic space may themselves pursue routinised modes of productivity, rather than those that are creative and radically innovative. Research Question B is thus introduced:

RQB: What is the relationship between HCI and productivity?

Research Questions A and B seek to investigate the relationships between technological propensity, HCI and productivity. Leahey (2006) suggests that gender differences may further impact academic research productivity. Gonzalez-Brambila and Veloso (2007) suggest that academic research productivity may differ depending on field of study (or area of expertise). Research Question C is thus introduced:

RQC: what are the interactive effects of gender and field of study on the relationships between technological propensity, HCI and productivity?

Innovation studies span from the national level to the level of the individual. King and Anderson (2004) introduce a typology of individual-level innovation facilitators, including personality, motivation, job characteristics and cognitive ability. An investigation of cognitive ability is beyond the scope of this research. The measurement of HCI (described above) is used in its place. However, differences in personality, motivation and job characteristics are investigated in this research, to further delineate the relationships around technological propensity, HCI and productivity. Personality is measured using a Five Factor Model of personality (Costa & McCrae, 1989), which comprises five dimensions of personality, including openness to experience, extraversion, conscientiousness, agreeableness and neuroticism. Motivation is measured using Schwartz's (1992) model of motivational values, which comprises four 'high-order' motivational values including self-transcendence, openness to change, conservation and self-enhancement. Job characteristics are investigated from the perspective of work climate perceptions (Scott & Bruce, 1994). A modified Organisational Climate Model (OCM) is used to investigate work climate perceptions. This model comprises two types of work climates, including the Internal Process Model (IPM) and the Open Systems Model (OSM). Thus, overarching research question of this study is introduced as follows.

> *What is the relationship between technological propensity, personality, motivational values, human capital investments (HCI), work climate perceptions, gender, field of study and productivity?*

Hypotheses and sub-hypotheses are derived from this overarching research question. To support an understanding of the theoretical model, these are outlined, in Table 1 as follows.

Table 1: Research questions and hypotheses of the study

Research Question	Hypothesis	Relationship
Research Question A		What is the relationship between technological propensity and productivity?
	Hypothesis A1	Technological propensity is significantly associated with productivity.
	Hypothesis A2	Personality is significantly associated with technological propensity.
	Hypothesis A2.1	Openness to experience is significantly associated with technological propensity
	Hypothesis A2.2	Extraversion is significantly associated with technological propensity
	Hypothesis A2.3	Conscientiousness is significantly associated with technological propensity
	Hypothesis A2.4	Agreeableness is significantly associated with technological propensity
	Hypothesis A2.5	Neuroticism is significantly associated with technological propensity
	Hypothesis A3	Motivational values are significantly associated with technological propensity
	Hypothesis A3.1	Self-transcendence is significantly associated with technological propensity
	Hypothesis A3.2	Openness to change is significantly associated with technological propensity
	Hypothesis A3.3	Conservation is significantly associated with technological propensity
	Hypothesis A3.4	Self-enhancement is significantly associated with technological propensity
	Hypothesis A4	Work climate perceptions are significantly associated with technological propensity
	Hypothesis A4.1	Open Systems Models (OSM) are significantly associated with technological propensity
	Hypothesis A4.2	Internal Process Models (IPM) are significantly associated with technological propensity
	Hypothesis A5	HCI are significantly associated with technological propensity
	Hypothesis A6	Personality mediates the relationship between technological propensity and productivity.
	Hypothesis A6.1	Openness to experience significantly mediates the relationship between technological propensity and productivity.
	Hypothesis A6.2	Extraversion significantly mediates the relationship between technological propensity and productivity.
	Hypothesis A6.3	Conscientiousness significantly mediates the relationship between technological propensity and productivity.
	Hypothesis A6.4	Agreeableness significantly mediates the relationship between technological propensity and productivity.
	Hypothesis A6.5	Neuroticism significantly mediates the relationship between technological propensity and productivity.

	Hypothesis	Relationship
	Hypothesis A7	Motivational values mediate the relationship between technological propensity and productivity.
	Hypothesis A7.1	Self-transcendence significantly mediates the relationship between technological propensity and productivity.
	Hypothesis A7.2	Openness to change significantly mediates the relationship between technological propensity and productivity.
	Hypothesis A7.3	Conservation significantly mediates the relationship between technological propensity and productivity.
	Hypothesis A7.4	Self-enhancement significantly mediates the relationship between technological propensity and productivity.
	Hypothesis A8	Work climate perceptions mediate the relationship between technological propensity and productivity.
	Hypothesis A8.1	Open Systems Models significantly mediate the relationship between technological propensity and productivity.
	Hypothesis A8.2	Internal Process Models significantly mediate the relationship between technological propensity and productivity.
	Hypothesis A9	Human Capital Investments (HCI) mediate the relationship between technological propensity and productivity.
Research Question B		What is the relationship between Human Capital Investments (HCI) and productivity?
	Hypothesis B1	HCI are significantly associated with productivity.
	Hypothesis B2	Personality mediates the relationship between HCI and productivity.
	Hypothesis B2.1	Openness to experience significantly mediates the relationship between HCI and productivity.
	Hypothesis B2.2	Extraversion significantly mediates the relationship between HCI and productivity.
	Hypothesis B2.3	Conscientiousness significantly mediates the relationship between HCI and productivity.
	Hypothesis B2.4	Agreeableness significantly mediates the relationship between HCI and productivity.
	Hypothesis B2.5	Neuroticism significantly mediates the relationship between HCI and productivity.
	Hypothesis B3	Motivational values mediate the relationship between HCI and productivity.
	Hypothesis B3.1	Self-transcendence mediates the relationship between HCI and productivity.
	Hypothesis B3.2	Openness to change mediate the relationship between HCI and productivity.
	Hypothesis B3.3	Conservation mediates the relationship between HCI and productivity.
	Hypothesis B3.4	Self-enhancement mediates the relationship between HCI and productivity.
	Hypothesis B4	Work climate perceptions mediate the relationship between HCI and productivity.
	Hypothesis B4.1	Open Systems Models mediate the relationship between HCI and productivity.
	Hypothesis B4.2	Internal Process Models mediate the relationship between HCI and productivity.

	Hypothesis	Relationship
Research Question C		What are the interactive effects of gender and field of study on the relationships between technological propensity, HCI and productivity?
	Hypothesis C1	Gender significantly moderates the relationship between technological propensity and productivity.
	Hypothesis C2	Field of Study significantly moderates the relationship between technological propensity and productivity.
	Hypothesis C3	Gender significantly moderates the relationship between HCI and productivity.
	Hypothesis C4	Field of Study significantly moderates the relationship between HCI and productivity.

For comparative insight, Studies 1, 2, and 3 all address the overarching research question, from different perspectives. Figure 1 below illustrates the theoretical model, which depicts the hypothesised relationships between the major variables under study. This model is built around the hypothesised association between technological propensity and productivity, represented by HA1. Research Question A also relates to the interrelationships around technological propensity and productivity. HA2, or the relationship between personality and technological propensity comprises of five sub-hypotheses, one for each of the components of the FFM model of personality. Each of these different components are expected to be associated with technological propensity in different ways. Given the underlying tenets of open innovation theory (Chesbrough, 2003a), openness to experience is expected to be positively associated with technological propensity. Neuroticism also commonly referred to as 'emotional instability' (Judge & Bono, 2001) however, may be negatively associated with technological propensity. The relationships between extraversion, conscientiousness and agreeableness and technological propensity may be expected either positive or negative, depending on a number of contextual factors. HA3 refers to the relationship between the components of Schwartz' (1992) model of motivational values. Each of the sub hypotheses under HA3 relate to each of the higher-order motivational values, identified by Schwartz. In the case of motivational values, self-transcendence and openness to change are expected to be positively associated with technological propensity, while self-enhancement and conservation would be expected to be negatively associated with technological propensity. HA4 relates to the relationships between the components of work climate perceptions (Patterson, et al., 2005) and technological propensity. Again, given the philosophy of open innovation (Chesbrough, 2003a), open systems climates would be expected to be positively associated with technological propensity while closed systems climates would be expected to be negatively associated with technological propensity. HA5 relates to the relationship between Human Capital Investments and technological propensity. Following Becker's (1964) seminal theory, the accumulation of Human Capital Investments is associated with a higher level of education, training and experience. Again, the relationship between HCI and technological propensity is unclear. Higher levels of HCI may contribute to either higher or lower levels of technological propensity, depending on the nature of the HCI accumulated and other contextual factors. HA6 relates to the mediating effect of personality on the relationship between technological propensity and productivity. Each of the sub-hypotheses under HA6 relate to each of the subcomponents of the FFM model of personality. Like HA2, each of these sub-components may have different mediating effects on the relationship in question. HA7 relates to the

mediating effect of motivational values on the relationship between technological propensity and productivity. The expected mediating effects of the different motivational values are expected to mirror the relationships hypothesised under HA3. The same applies to HA8, which relates to the mediating effect of work climate perceptions on the relationship between technological propensity and productivity and HA9, which relates to the mediating effect of Human Capital Investments on the relationship between technological propensity and productivity.

Research Question B relates to the relationship between Human Capital Investments and productivity. As previously discussed, Human Capital Investments refers to intangible individual-level investments in human capital, such as education, training and experience. Following (Becker, 1964), higher levels of HCI are expected to be positively associated with productivity. However, this relationship may differ according to context. For example, more experienced academic researchers may experience decreases in productivity (Gonzalez-Brambila & Veloso, 2007). HB2 relates to the mediating effect of personality on the relationship between HCI and productivity. Each of the sub-components of personality are tested individually, as sub-hypotheses. HB3 and HB4 relates to the mediating effect of motivational values and work climate perceptions on the relationship between HCI and productivity, respectively.

Research Question C relates to the interactive effects of gender and field of study on the relationships between technological propensity, HCI and productivity, respectively. HC1 is related is the interactive effect of gender on these relationships, while HC2 is related to the interactive effect of field of study on these relationships. Figure 1 below provides a diagrammatic representation of these hypothesised relationships. Given that some relationships may be either negative or positive, all relationships are depicted with arrows in both directions.

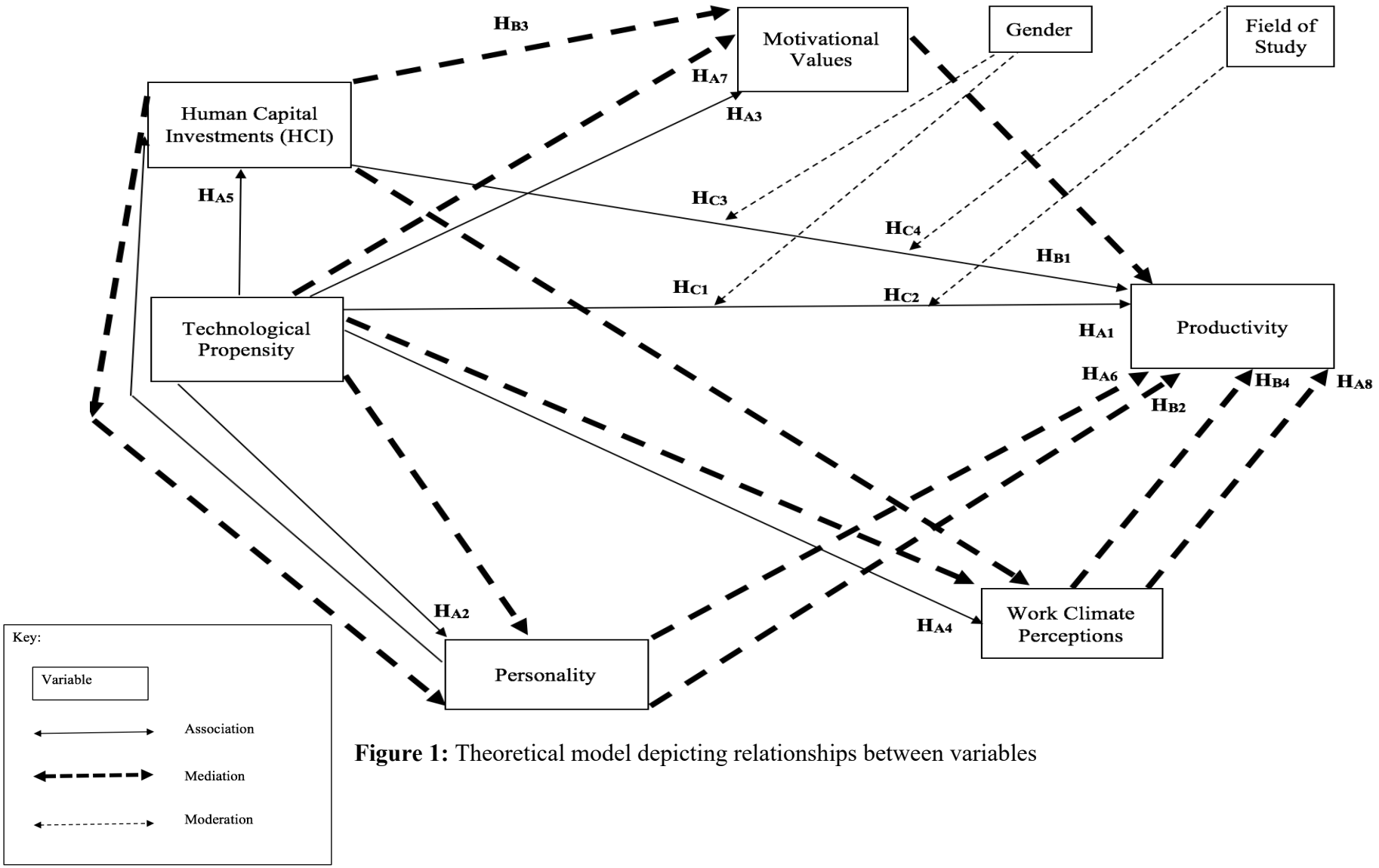


Figure 1: Theoretical model depicting relationships between variables

The relationship between HCI and productivity is also to be investigated, to assess the impact of education, training and experience on productivity, represented by HB1. The associations between technological propensity and personality (HA2), motivational values (HA3), work climate perceptions (HA4) and HCI (HA5) are all represented above. The mediating effects of personality (HA6), motivational values (HA7), climate perceptions (HA8) and HCI (HA9) on the relationship between technological propensity and productivity are also represented above. Building on HB1, the mediating effects of personality (HB2), motivational values (HB3) and work climate perceptions (HB4) are represented above. Finally, the moderating effects of gender and field of study on HA1 and HB1 are represented by HC1, HC2, HC3 and HC4, respectively. The chapter sequence of this thesis is now briefly discussed.

1.7. CHAPTER SEQUENCE

Each of the chapters of this study is briefly described below. Thereafter, this chapter is concluded.

Chapter 1: Introduction. In this chapter, the background to the study is outlined and the theoretical framework of the research is introduced. The lack of knowledge of the potential impact of certain new technological and methodological advances in the context of academic research highlighted as a core aspect of the problem addressed in this research. The tensions between the concepts of innovation failure (McKenna, 2014), academic routinisation (Anderson, de Dreu & Nijstadt, 2002) and the extent of global societally-consequential problems are introduced as the literary tension that this study seeks to address. The measurement of individual-level innovation, as per a modified version of King and Anderson's (2002) typology of KSOAs is introduced as the theoretical framework upon which this research is based. The theoretical roles of personality, motivational values, climate perceptions, human capital investments, gender and field of study are all introduced and briefly discussed. A brief overview of the methodological process adhered to in this research is provided. The research problem, research questions, aim of the research, research objectives, research questions and derived hypotheses are all thereafter introduced and a diagrammatic representation of the interrelationships between the variables under study is also provided. The chapter concludes with a summary of the chapter sequence of this thesis.

Chapter 2: Literature Review. This chapter provides an overarching and broad review of the pertinent literature relating to the variables under study. An examination of seminal innovation management and knowledge management theory is provided. Historical and global trends of knowledge, science and innovation are discussed. The interrelations between these theories are linked to 6G innovation theory; which is considered a culmination of the evolution of knowledge and innovation. The 6G and probabilistic innovation literature is then reviewed. The emergent technologies and methodologies associated with 6G innovation, including open innovation and crowdsourcing are introduced and discussed. Technological propensity, a behavioural orientation which measures the extent to which individuals seize opportunities related to certain new modes of productivity, and which offer significant economies of scale, is introduced and discussed. The hypothesised relationship between technological propensity and productivity is delineated. This is followed by a discussion of certain individual-level variables that are purported to account for individual differences in the relationship between technological propensity and productivity, and the derivation of testable hypotheses based on literature. Firstly, personality, in terms of the Five Factor Model (Costa & McCrae, 1989) is considered. Second, Schwartz's (1992) theory of motivational values is described. Thirdly, work climate perceptions are considered, in conjunction with a review of Patterson, et al.'s, (2005) Organisational Climate Model (OCM). Human capital investments (HCI) are discussed next, and the relationships around HCI, technological propensity and productivity are explored. Finally, differences in gender and field of study (or area of expertise) are considered, in their relationship to technological propensity, HCI and productivity. This chapter is then concluded. An introduction to the next chapter follows.

Chapter 3: Methodology. This chapter introduces and describes the methodology followed in this research. Firstly, a brief overview of the methodology chapter is provided. Thereafter, a discussion pertaining to the paradigmatic location of the research follows. Given that this research employs a mixed methods approach, this research is located in a pragmatic research paradigm. Next, use of a mixed methodology is justified, owing to the pluralistic nature of the research. The benefits associated with this approach are described. The process the qualitative research is described next. This includes discussion on the specification of the sampling process, the processes of data collection, verification and coding. The use of each method described is justified by reference to previous studies and literature. Details pertaining to both quantitative studies are discussed next. These include the research design and scope of each study, as well as details of the populations, samples and the confidence levels used for statistical

testing. A discussion on reliability and validity follows and the process undertaken during pilot studies is reviewed. Again, the use of each method described is justified by reference to previous studies and literature. Subsequently, the research instruments are considered. This includes an interview schedule used for qualitative research (Study 1) and two questionnaires, used for Studies 2 and 3. The derivation of the questions contained in the interview schedule is reviewed. Each of the scales contained in the questionnaires are described in relation to literature. The procedure of data collection and analysis is then described. An explanation of the data analysis in terms of the derived hypotheses is also provided. The statistical methods undertaken to analyse quantitative data are detailed, with reference to previous studies of a similar nature. Ethical considerations and limitations are considered, and the chapter is concluded.

Chapter 4: Qualitative Results. This chapter reports the results of the inductive, qualitative analysis, also referred to as Study 1, and provides models of the interrelationships between themes. The relationships between qualitative themes are stated as derived propositions. The results of this analysis are only reported in this chapter and discussed in greater detail in Chapter 6. Following the method prescribed by Miles and Huberman (1994) and Miles, Huberman and Saldana (2014), interview transcripts were analysed for thematic commonalities. Themes were grouped together by codes. The findings of the qualitative analysis suggest that breakthrough research productivity (BRP) is driven by a combination of internal and external drivers. According to these findings, internal drivers of BRP include technological propensity, personality, motivation, and innate abilities. External drivers of BRP include work climate, resource availability and human capital investments. Each theme and code is described, with reference to pertinent quotes extracted from raw data (interview transcripts), used as supporting examples. Propositions are derived from the relationships between themes. Thereafter, models of emergent inter-relationships are constructed, based on the derived propositions. These include a model of internal drivers of BRP, a model of external drivers of BRP and a model comprising both internal and external drivers of BRP. It is discovered that both internal and external drivers of BRP tend to converge around the notion of 'openness'. The model of internal and external drivers of BRP is then compared and contrasted to the theoretical model derived from the literature. This chapter is then concluded, and the results of the quantitative studies follow.

Chapter 5: Quantitative Results. In this chapter, the results of the quantitative portions of this research are reported. Again, this chapter contains a reporting of results only. Results are discussed in Chapter 6. This chapter reports the results of both Studies 2 and 3. The results of Study 2, which involves the analysis of data gathered from a sample of academic researchers, are reported first. This includes a report of univariate, descriptive statistics, including measures, locations, central tendencies and statistical dispersions. Bivariate associations between variables are considered. Thereafter, the results of tests of discriminant and convergent validity are provided. Next, the results of the hypothesis testing, by way of multivariate analyses are reviewed. This includes tests of hierarchical multiple regression, tests of mediation and tests of moderation. Following the conclusion of reporting of results of Study 1, the results of Study 2 are reported. Study 2 involves the analysis of data gathered from a sample of crowd-workers. Again, the results of the univariate, bivariate and multivariate analyses are provided, respectively. This chapter concludes with a summarised report of the results of all hypothesis tests and an introduction to Chapter 6.

Chapter 6: Discussion. In this chapter, the qualitative results of Study 1, 2 and 3 are discussed in relation to each other, and in relation to literature. This chapter is structured into three sections. In the first section, the results of the qualitative analysis are discussed in relation to literature. This discussion is structured around the propositions derived in Chapter 4. The second section of this chapter contains a discussion of the quantitative findings of Studies 2 and 3. This discussion is structured according to the hypotheses derived from the literature, which were subsequently tested during quantitative analysis. In the third and final section of this chapter, the results of Studies 1, 2 and 3 are discussed in relation to literature, in a synthesis of qualitative and quantitative results. This section is structured in a combination of propositions and hypotheses and identifies similarities and differences between each of the three studies and literature. This chapter is then concluded, and the final chapter is introduced.

Chapter 7: Conclusion. In this chapter, the results of this research are summarised, reported and discussed, to offer an outline of the research. First a summary of the research objectives is outlined. Next, a summary of the research findings and recommendations is provided. In this section, attempts are made to answer to each of the research questions and to provide practical managerial recommendations based on these findings. Finally, the implications of the research findings and recommendations for further research are reviewed, and the chapter is concluded.

1.8 CHAPTER CONCLUSION

In this chapter, the background to the study, research problems and research questions were presented. An introduction was offered, to the theoretical tension between the predictions of innovation theory and the problems of knowledge aggregation and innovation routinisation. The principles surrounding Callaghan's (2014a) theory of 6G innovation and probabilistic innovation were introduced and located in relation to seminal innovation management theory. Given the predictions of 6G innovation theory, it is argued that the extent to which individuals seize opportunities associated with certain new modes of production, specifically those that offer significant economies of scale, may be related to productivity. This argument forms the foundation of this thesis. A brief methodological overview was provided, in which three different studies are introduced. Study 1 is a qualitative study which involves qualitative interviews with award winning scientists, innovators and academic researchers. Study 2 involves the quantitative analysis of data collected from a sample of South African academic researchers. Study 3 involves the quantitative analysis of data collected from a sample of crowd-workers. Thereafter the research problem, the aim of the research, the objectives of the research, the research questions and derived hypotheses, were introduced, respectively. A diagrammatic representation of the hypothesised relationships between the variables under study was provided and discussed. This chapter was concluded with chapter summaries which outline each subsequent chapter in this thesis. A review of the literature now follows.

CHAPTER 2
LITERATURE REVIEW

2.1 INTRODUCTION AND STRUCTURE

In this chapter, literature is reviewed, and hypotheses are derived. The previous chapter introduced a theoretical model depicting relationships between variables. This chapter extends the previous chapter by a discussion of seminal literature and theory. The chapter is structured into four interlinking sections, as follows.

In the first section seminal knowledge and innovation literature is discussed in the context of this research. An overview of 6G theory innovation is provided. According to Callaghan (2014a), 6G (Sixth Generation Innovation) represents a new perspective of knowledge and innovation management, that may provide significant scale advantages.

In the second section, the function of management as a science, and the multi-disciplinary nature of the interface of management, is discussed. This study is then located in relation to seminal innovation and knowledge management literature. Next, theory pertaining to innovation management and 'breakthroughs' is considered. The close association between innovation and knowledge management is reviewed. The problem of knowledge aggregation is described. Thereafter, a historical overview of innovation is provided, with reference to Rothwell's (1994) 5G model of innovation. The evolution of 5G innovation and the emergence of 6G innovation is then examined.

In the third section, 6G theory is discussed in further detail. 6G theory is premised on the notion of 'innovation failure', which is defined and discussed. According to Callaghan (2014a), the application of 6G innovation management may offer solutions to innovation failure and the problem of knowledge aggregation. This section also contains a discussion on probabilistic innovation, a form of innovation that exploits scale opportunities afforded by certain new technologies, such as the Internet. A more detailed discussion pertaining to different types of 6G technologies and methodologies follows. These include crowdsourcing and crowdfunding.

In the fourth, and final section, it is argued that the adoption of 6G innovation management may enhance the innovative potential of scientific and academic research. Specifically, it is argued that the adoption of '6G practice' may enhance the innovativeness of academic research output. Furthermore, it is argued that the adoption of 6G practice, in the academic context may stimulate the production of 'breakthrough' research outputs, specifically those that offer social

externalities. The relationship between 6G adoption and innovative research performance (or, 'breakthrough research productivity') is delineated. This proposed relationship forms the foundation of this research. The potential consequences of this relationship are discussed. Because this research is conducted at the level of the individual, individual-level differentiators are considered. These are referred to as human resources management (HRM) determinants. It is argued that differences in HRM determinants may impact the relationship between 6G adoption and research performance. These include i) personality, ii) motivational values, iii) work climate perceptions, iv) human capital investments (HCI), v) gender and vi) field of study. Each of these is discussed. This chapter is then concluded with a summary. An introductory, historical overview of innovation and knowledge management now follows.

2.2 TOWARDS A SIXTH GENERATION OF INNOVATION: THE EVOLUTION OF KNOWLEDGE AND INNOVATION

Since its conception, the fundamental tenets of Darwin's (1859) seminal theory of evolution have been used to describe phenomena in a vast range of scientific fields of inquiry. This is referred to as universal Darwinism, a term used to describe approaches that extend the theory of Darwinism beyond its original domain, of biological evolution (von Sydow, 2012). Universal Darwinism posits that the mechanisms of variation, selection and heredity are generalisable, and therefore can be applied to explain evolution in a wide variety of other domains, including psychology, economics, culture, medicine, computer science and physics (Hodgson, 2005). It has been argued that scientific research itself is subject to the principles of evolution (Abelson, 1993). This is because science, the systematic study of the universe (Willson, 1999), is a complex system, which has over time, mutated, progressed and evolved towards a theorised 'perfect state' (Russell, 2015). Mitchell and Taylor (1999, p. 7) describe evolution as "a method for searching among an enormous number of possibilities for 'solutions… a method for designing innovative solutions to complex problems, where the search space is the collection of all possible [solutions] – an infinite set of possibilities".

Similarly, Kuhn (1970) suggests that scientific fields undergo periodic paradigm shifts, rather than solely progressing in a linear and continuous fashion. These paradigm shifts open up new approaches to understanding what may have never been considered valid before (Crilly, 2010). In this way, the Kuhnian perspective of scientific progress might be likened to the process of evolution. Like the evolution of complex natural systems, novel developments (or,

innovations), that produce desired advancements are favoured, while those that do not are discarded.

In this section, the theory of universal Darwinism is applied to the evolution of science, industry, society, technology and innovation. It is argued that these have co-evolved through innovation, and that knowledge is the proverbial DNA that binds them together. It is also proposed that these co-evolutionary processes have reached a point of convergence, and that a new paradigm of management may be required, to harness the full potential of new developments that have arisen. In doing so, it may be possible to address certain problems, that previously may have been difficult, or perhaps impossible to solve.

Gray (2009) classifies the evolution of science by defining four interlinking 'generations' of scientific inquiry. According to this classification, the initial (first) generation of science was primarily empirical, in that it aimed to describe natural phenomena. The subsequent (second) generation of science was primarily theoretical in nature, using models and generalisations as tools to uncover truths. The third generation of science invoked the use of computational techniques to focus on stimulating complex phenomena. Finally, the fourth, or current generation of science uses data exploration, where data is captured by instruments or simulated and processed by software, to unify theory. This current, '4th Generation' is conceptualised as a new paradigm of science that is data intensive. This paradigm is purported to have emerged as a result of rapidly accelerating changes in information and communication technologies (ICT), such as the Internet, social media and smart-technology. For Gray (2009, p. xv), the emergence of these new technologies will "increase the 'information velocity' of the sciences and will improve scientific productivity of researchers".

According to Kitchin (2014, p. 3), the emerge of Big Data, along with significant advancements in data analytics have given rise to "paradigm shifts across multiple disciplines". In this context, Big Data is defined as "large volume, complex, growing data sets with multiple, autonomous sources" (Wu, Zhu, Wu & Ding, 2014, p. 101). Crawford (2011) defines Big Data as the use of predictive analytics, that extract value from extremely large data sets. These analyses can be used to "spot business trends, prevent diseases [and] combat crime" (Cukier, 2010). For Kitchin (2014), these advancements represent disruptive innovations, which have helped to propel the evolution of scientific research into new, unchartered territory, where the development of theory that is trans-dimensional and trans-disciplinary has become enabled.

The advent of Big Data has also coincided with the emergence of electronic Science (or eScience). The term eScience refers to science that makes use of new technological advances to analyse data and conduct experiments, that may have previously not been possible, due to the magnitude of the data sets involved (Taylor, Deelman, Gannon & Shields, 2014). The successful integration of Big Data and eScience have produced significant advancements in meteorology, genomics, complex physics simulations, biology and environmental research (Reichmann, Jones & Schildhauer, 2011; Callaghan, 2018a). These examples, amongst others, may represent a point of convergence, where scientific data is seamlessly integrated with literature; a state in which interconnectivity in scientific research is 'complete' (Gray, 2009). Roco (2002; p. 9) provides a definition of convergence, in the context of technological integration:

> "[Convergence refers to] deep integration of knowledge, tools, and all relevant activities of human activity for a common goal, to allow society to answer new questions to change the respective physical or social ecosystem. Such changes in the respective ecosystem open new trends, pathways, and opportunities in the following divergent phase of the process."

Essentially, the emergence of Big Data and Big Data analytics, made possible through the integration of emergent technologies, is an example of scientific advancement that may have radically altered the state of science itself. The impact of the evolution of these scientific and technological evolutionary outcomes (such as Big Data and eScience) has been widespread and global, leaving its mark on almost every facet of human life (Bostrom, 2014; Kurzweil, 2016). Some technological advancements have had detrimental social consequences (Bostrom, 2014; Callaghan, 2018b), such as climate change and the degradation of the natural environment (Bostrom, 2014; Maibach, Myers, Leiserowitz, 2016). Others have produced significant social opportunities and advantages (Smith, 2010), such as advancements in medical and health research (Moses, Matheson, Cairns-Smith, George, Palisch & Dorsey, 2016) and environmental conservation (Asensio & Delmas, 2016). Rapid and radical advances and mutations in technology, global connectivity, trade and the movement of capital, people and information, has reconfigured almost all sectors of the global economy (Dobbs, Manvika & Woetzel, 2015). Christensen, Raynor and McDonald (2015) use the term 'disruptive innovation' to describe those radical innovations that introduce drastic shifts in the business environment. Although the Disruptive Innovation Model (Christensen, 1997; Christensen,

Raynor & McDonald, 2015) is related primarily to innovation in the business context, its tenets may be applicable in other domains (Christensen & Eyring, 2011).

The co-evolution of science, technology and society can also be classified in terms of industry. The Fourth Industrial Revolution (4IR) is the fourth major industrial era, since the initial Industrial Revolution, of the eighteenth century (Schwab, 2017). The 4IR is described as a range of new technologies, that fuse the physical, digital and biological worlds, and which may impact all disciplines, economies and industries (Schwab & Samans, 2016). Schwab and Samans (2016, p. 1) refer to the 4IR in terms of "emerging technology breakthroughs, such as artificial intelligence (AI), robotics, the Internet of Things, autonomous vehicles, 3D printing, quantum computing and nanotechnology".

It is argued that the progress of these evolutionary processes, whether scientific, technological, social, or industrial, is dependent on innovation, which in turn is dependent on knowledge. Smith (2010; p. 6) defines as innovation as the result of "the interaction of diverse knowledge inputs." In this sense, knowledge and innovation are intrinsically tethered to one another. Knowledge may function as a catalyst that triggers innovation. In turn, innovation may function as a catalyst that triggers the evolutionary, or paradigm shifts described above.

Rothwell (1994) provides a historical overview of innovation, known as the 'Five Generation' (or 5G) model of innovation. The 5G model is comprised of five chronological and interlinking generations of innovation. The first of these (1G) is purported to have commenced at the conclusion of World War II. Rothwell (1994) conceptualises the most recent, 5th generation of innovation in (5G) relation to the increasing complexity and rates of technological change. These changes have, over time, required more extensive vertical and horizontal alliances and more flexible and efficient responses to market changes for firms. 5G is purported to have commenced in the early 1990's, but it's end point is undefined. The key aspects of the present, or 5th Generation of innovation includes; integration, flexibility, networking, real-time/parallel information processing and reflects a "more comprehensive process of the electronification of innovation across the whole innovation system" (Rothwell, 1994, p. 25). Both Rothwell (1994) and Smith (2010) conceptualise industrial innovation as a learning process, where knowledge is accumulated through internal and external learning. Christensen, Raynor and McDonald (2015) further conceptualise disruption in the innovation process itself as a cyclical process. In

this sense, changes in the processes of innovation may be driven by disruptive innovations themselves.

For Drucker (1994, p. 12), "the basic economic resource – the means of production – is no longer capital, nor natural resources, nor labour. It is and will be knowledge." In this context, knowledge is defined as the "dynamic human process of justifying personal beliefs towards truth" (Nonaka, 1994, p. 6). It is proposed therefore, that knowledge lies at the heart of these economic, social, technological and scientific revolutions and paradigm shifts, described above. With knowledge as a common thread, the progression of innovation, industry and science have followed similar paths. Callaghan (2017a) introduces the notion of a Sixth Generation of innovation (6G), which is purported to have evolved from the preceding 5th Generation, and represents the culmination of 5th Generation Innovation, 4th Generation science and 4IR. Callaghan (2017a) predicts that further evolutionary progress may result in a 7th Generation of innovation, in the future. These associations are depicted in Figure 2, below.

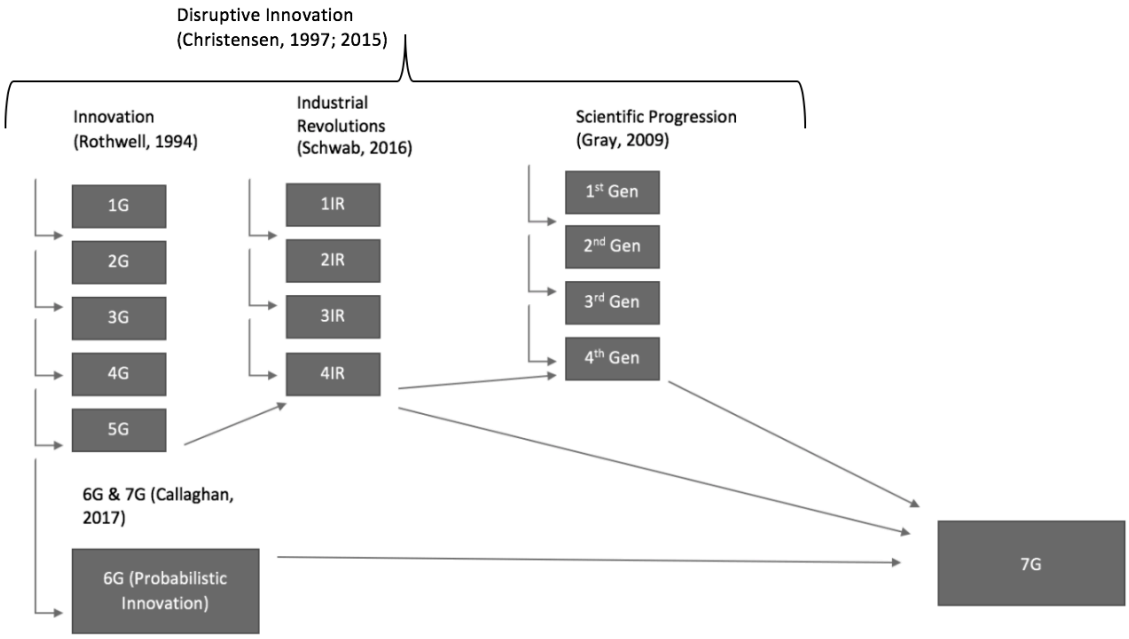


Figure 2: The evolution of knowledge and innovation (Source: Author)

In summary, knowledge may therefore be considered the foundation of scientific progress. Knowledge has emerged as the basic economic resource (Drucker, 1994), and the interaction of diverse knowledge generates innovation (Smith, 2010). It is argued therefore, that

knowledge functions as the adhesive, that holds the evolution of these processes together, and catalyses and advances the associations between them, through innovation.

A rapidly growing body of literature has begun to unravel the intricacies of these relationships, and the importance of knowledge, in precipitating these evolutionary advancements, which occur through innovation. Chesbrough (2003) posits that by allowing knowledge to flow inside and outside of organisational boundaries, structural changes to knowledge aggregation may result in higher quantities and quality of innovation. This process is referred to as open innovation and has seen significant traction in recent years (de Araujo Burcharth, Knudsen & Sondergaard, 2014; Chesbrough, 2017). Surowiecki (2004) suggests that harnessing 'the wisdom of crowds', or the collective wisdom of large numbers of people, dispersed across different geographical locations, can result in highly accurate predictions and efficient decision-making, sometimes to a greater extent than the experts. Wooley et al., (2010) investigate the collective intelligence of crowds, or large groups of people and discover that crowds can often outperform highly trained specialists and experts. These new methodologies of knowledge aggregation differ from previous modes of innovation in that they include the interactions of both explicit, and tacit knowledge sources. Explicit sources of knowledge are embedded or codified in artefacts and are easy to find and move (Kane, 2012). By contrast, tacit knowledge defies recording; it is embedded within individuals and underlies personal skill (Wyatt, 2012). Unlike explicit knowledge, tacit knowledge is very difficult to move from where it originated (von Hippel, 1976). However, new forms of knowledge aggregation may offer a mechanism which would allow the easy transfer of both explicit and tacit knowledge (Callaghan, 2014a), which may result in smoother knowledge interactions, and ultimately, a higher probability of producing innovations.

These philosophies centre on a new form of knowledge aggregation; one which occurs almost in real-time and which may hold significant scale advantages. Collectively, these are referred to as 'crowdsourcing'. Howe (2006, p. 1) defines crowdsourcing as the "act of outsourcing functions to undefined and generally large networks of people in the form of an open call." For Brabham (2008, p. 75), crowdsourcing represents an "online distributed problem-solving and production model." Organisational adoption and implementation of crowdsourcing may result in significantly improved costs, speed, quality, flexibility, scalability and diversity of work projects, that ordinarily would have been completed by experts only (Brabham, 2013). Estelle-

Arolas and Gonzalez-Ladron De Gueara (2012, p. 190) seek to provide an integrated definition of crowdsourcing, and conclude the following:

> "Crowdsourcing is a type of participative online activity in which an individual, an institution, a non-profit organisation, or company proposes to a group of individuals of varying knowledge, heterogeneity, and number, via a flexible open call, the voluntary undertaking of a task. The undertaking of the task; of variable complexity and modularity, and; in which the crowd should participate, bringing their work, money, knowledge and/or experience, always entails mutual benefit. The user will receive the satisfaction of a given type of need, be it economic, social recognition, self-esteem, or the development of individual skills, while the crowdsourcer will obtain and use to their advantage that which the user has brought to the venture, whose form will depend on the type of activity undertaken".

Building on the commonalities that underlie these streams of literature, Callaghan (2014a) posits that a new generation of innovation, Research and Development (R&D), science and industry has begun to emerge. Founded primarily on Rothwell's (1994) 5G model, Callaghan (2017c) suggests that a sixth generation (6G) of innovation is presently underway. The term 6G is used as an umbrella term, to refer to the use of new and emerging technologies and methodologies such as crowdsourcing, crowdfunding, open innovation, collective intelligence, citizen science and probabilistic innovation (PI). 6G may be uniquely suited to solving research problems, that under other paradigms, would either be very difficult to solve, or entirely unsolvable (Callaghan, 2014a; 2014b; 2015a). Probabilistic innovation forms the foundation of 6G theory. Probabilistic innovation is built on the premise that exponential increases in problem solving inputs may result in exponential solution output potential (Callaghan, 2015a). In PI theory, large volumes of data, gathered from large and open collectives (crowds) of people, can be used to increase the probability of solving a research problem. Callaghan, (2015c) argues that PI is uniquely suited to solving problems with societal consequence, such as disease, pharmaceutical development and drug discovery, because it is independent of traditional profitability constraints. Furthermore, PI may enable 'near real-time' productivity through the use of new technologies, such as the Internet and social networks. While closed models of innovation rely primarily on individuals or relatively small groups individuals to solve problems (Chesbrough, 2003a), 6G theory adopts an open innovation philosophy. 6G differs from open innovation however, in that it seeks to obtain knowledge inputs from both expert and unconventional, non-expert sources. It also seeks to obtain knowledge inputs from both tacit and explicit sources. In this way, 6G may offer the opportunity to maximise

economies of scale, and to open the innovation process fully, by leveraging communities as innovation engines (Callaghan, 2017c).

Collective problem solving has repeatedly demonstrated proof of concept. Significant advances have been made in a diverse array of scientific fields of enquiry. Collective problem solving has also been harnessed to significant effect in a broad variety of business-related undertakings. Some examples include medical, bio-medical and health research (Swan, 2012a); disaster management (Goodchild & Glennon, 2010); drug and pharmaceutical development (Torr-Brown, 2013); software development (Lakhani & Panetta, 2007); computer science (Rosenberg, 2016); geological research (Buecheler, Sieg, Füchslin & Pfeifer, 2010); climate change (Knox, Hess, Daccache & Wheeler, 2012); meteorology (Overeem et al., 2013); biodiversity (Freeland, 2011); film production (Sørenson, 2012); fast moving consumer goods production (Sciaca, 2016) and financial services (Chan, Yim & Lam, 2010). The potential applications of new methodologies related to 6G innovation are vast, and the potential benefits immeasurable. Callaghan (2017c) argues that 6G and PI can and should be systematised to harness their full potential. The theory that underlies 6G innovation is covered in greater detail, further in this chapter.

As per the above-mentioned examples, successes in the use of crowd-based methodologies in commercial, private, or for-profit R&D are vast. However, there is a dearth of research that examines the potential of these new modes of innovation in the context of academic research. In the context of this research, 'academic research' refers to research that is conducted for strictly academic purposes, by academic researchers who are employed by public institutions, such as universities and colleges. In contrast, commercial, or private research and R&D is primarily conducted for the purpose of profit, by private organisations. For Price (2015), the differences between academic research and commercial R&D are stark, particularly what are often significant differences in research methodology, aims and purposes, funding models, infrastructure and impact. While academic research is commonly undertaken in order to contribute to existing knowledge or to address a gap in existing knowledge (Kothari, 2004), commercial R&D (also referred to as 'applied research) is more commonly undertaken to fulfil specific organisational objectives. Examples of commercial research include market research, which is often undertaken to identify market trends (Brace, 2018) or product development R&D which is typically undertaken to improve performance features of an organisation's commercial offerings (Hakansson, 2015). This study hopes to address this gap in the literature,

by investigating the potential of new, probabilistic approaches to innovation, as applied to academic research, rather than commercial or private R&D.

Unlike private, or commercial R&D, it has also been argued that academic researchers are bound by a moral responsibility to societal stakeholders; to find solutions to problems which may have societal consequence (Jaffe, 1989; Radder, 2010; Fenton, Chillag & Michael, 2015). Harris (2005, p. 242) suggests that there is a "moral obligation to undertake, support and participate in serious scientific research." Academic research and commercial, or private R&D do share many commonalities. For instance, both forms of research seek to apply the scientific method to find solutions to problems. Most notable of these commonalities however, is that both forms of research have long prescribed to closed models of innovation (Chesbrough, 2003a, Campanario, 2009), and that paradigmatic conformity may, in both cases, constrain innovation rather than stimulating it (Kuhn, 1970). This does not imply that scientific research is void of innovation. Rather, that the application of new, probabilistic methodologies may enable scale advantages, which could increase the rate at which important, social innovations are produced. For Callaghan (2017c), 6G represents a present point of convergence, but that a future Seventh Generation of Innovation (7G) is yet to emerge. 7G represents a future convergence of industry, science, technology, R&D and knowledge beyond that of what is presently possible (see Figure 2 depicting the co-evolution of knowledge and innovation). 7G innovation is however beyond the scope of this research. This study focuses on new technologies and methodologies that fall under the 6th Generation, probabilistic innovation paradigm, and their potential applications in academic research. Having provided the historical background to the literature, a discussion of relevant preceding, or antecedent theory, of both knowledge management and innovation management, now follows.

2.3 ANTECEDENT THEORY: THE MANAGEMENT OF KNOWLEDGE AND INNOVATION

The process of evolution requires no central authority. Management, as a scientific discipline however, may function as a useful mechanism to prod the evolutionary process in desirable directions. This is because management is inherently transdisciplinary in nature (Smith, 2010), and may therefore hold the unique ability to act as an interface between other disciplines. The principles of classic scientific management theory (Waring, 2016) still hold as the adhesive mechanism that contain a threefold ability to organise, plan and control processes, through

precise and rigorous scientific measurement methods (Smith, 2010; Waring, 2016). This research therefore, is conceived through the lens of management. More specifically, this research is conceived through a trans-contextual lens, of knowledge management, innovation management and human resources (HR) management. In other words, this research is simultaneously conceived through a number of different perspectives, in the hope that this approach will provide a holistic, multi-dimensional perspective on the relationships in question.

Each of these forms of management are directly related to probabilistic innovation theory. PI theory is premised on the notion that exponential increase in knowledge inputs may enhance the rate at which knowledge interactions occur, and this may, in turn, lead to an exponential increase in innovation, or problem-solving capacity (Callaghan, 2014a). Essentially, PI theory predicts that the adoption and implementation of new technologies and methodologies, which offer significant economies of scale, may lead to an enhanced problem-solving capacity.

Furthermore, a trans-contextual approach is adopted to allow for a multifaceted management theory perspective. Each of these areas of management theory contribute a different perspective, each of which may provide valuable insights that the others may not. For example, knowledge management refers to a multi-disciplinary process of capturing, developing, sharing and effectively using knowledge to achieve objectives (Nonaka, 1994). Knowledge management may therefore offer a useful perspective on the use of knowledge in the context of PI. Innovation management refers to the management of the subsequent outcomes of knowledge management (Crossan & Apaydin, 2010), namely; innovation. HR management is primarily concerned with the management of people, to improve performance, in line with objectives (Collings & Wood, 2009). The relation between PI and HR management is discussed further in Section 2.5 of this chapter. Knowledge management and the problem of knowledge aggregation are discussed next.

2.3.1 Knowledge Management and the Problem of Knowledge Aggregation

Knowledge management refers to the process of creating, sharing, using and managing knowledge and information (Girard, 2015). Knowledge management typically involves a multi-disciplinary approach to achieving organisational objectives. In the organisational

context, knowledge is often considered a strategic asset (Maier, 2007). In the academic research context however, knowledge represents the foundation of scientific progress (Radder, 2010).

For Nonaka (1994, p. 6), knowledge represents the "dynamic human process of justifying personal beliefs towards truth." In this context, Drucker (1987, 1994, 1999) posits that knowledge has replaced traditional economic resources, such as capital and labour, as the primary means of production. As a result, a new knowledge-based economy has emerged, comprised of knowledge-based organisations. Knowledge-based organisations are, in turn, comprised of knowledge workers; "specialists who direct and discipline their own performance, through organised feedback" (Drucker, 1987, p. 13).

Building on the premise of knowledge as the "fuel for innovation" (Nonaka, 1994, p. 16), the knowledge worker is therefore the human component of organisational capital, that holds the potential to provide impetus as "agents for change", or innovation (Nonaka, 1994, 16), in a knowledge economy. At the core of this prediction lies the argument that "converting data into information requires knowledge and knowledge, by definition, is specialised" (Drucker, 1987, p. 93).

Drucker (1987, p. 95) also successfully predicts the advancement of technology, necessitating analysis and diagnosis of data generated, before it becomes "too large to handle." This is an issue which has become abundantly evident in the eras of crowdsourcing (Howe, 2006) and Big Data (McAfee et al., 2012). Indeed, the dawn of the Information Age has been mirrored by a parallel shift in economics (Castells, 2010; Vu, 2011). Over the course of these shifts, the productivity of knowledge has become a crucial factor in firm success (Holsapple & Wu, 2011). The advent of rapidly evolving information and communication technologies (ICT) has propelled the global movement and availability of information and knowledge, across boundaries previously considered impenetrable, at an exponentially increasing rate (Zelenika & Pearce, 2013; Dalkir & Beaulieu, 2017). These technological advancements have resulted in an explosion of new technological breakthroughs (Christensen, Raynor & McDonald 2015), which have had profound global economic and social consequences.

Despite these significant advances however, some barriers to the efficient and effective transition of knowledge have not yet been overcome. Collins (2010) differentiates between explicit and tacit knowledge. Explicit knowledge is knowledge that codified, and that is easy

to access or transfer. By contrast, tacit knowledge resides within the individual, and is therefore difficult to move or transfer (von Hippel, 1976, 1994). A large portion of scientific knowledge may exist primarily in the form of tacit knowledge, in the minds of expert scientists and may therefore not be easily accessible (Nonak & Von Krogh, 2009; Collins, 2010). The prevalence of tacit knowledge, and the difficulty in moving or transferring it, is an example of the problem of knowledge aggregation.

The knowledge aggregation problem relates to the difficulty in precipitating knowledge interactions to generate innovation and subsequently, breakthroughs (Smith, 2010). Despite the exponential availability of knowledge inputs available through modern ICT, innovation may often be constricted by models of market profitability (McKenna, 2014). These impediments can be attributed to three theoretical assertions. Firstly, that knowledge is proprietary (organisation specific) and is unevenly distributed (Hayek, 1945). Secondly, that knowledge is inherently decentralised (von Hippel, 1976). Thirdly, that knowledge is 'sticky' (Polanyi, 1973); it resides within individuals as tacit knowledge rather than within organisations and is very difficult and costly to move from where it originated (Nonaka, 1994). These constraints form a threshold to knowledge creation and transfer, and collectively are referred to as the 'problem of knowledge aggregation' (Grant, 1996; Lam, 2000; Smith, 2010).

The problem of knowledge aggregation is further compounded in the case of commercial, private or 'for-profit' R&D. This is of particular concern in fields such as biomedical and pharmaceutical R&D, which are often coupled to the dictates of the market mechanism; in a word, profitability (Nathan & Goldberg, 2005; Enkel, Gassman & Chesbrough, 2009). Investments in biomedical or pharmaceutical R&D are characteristically linked to profit-driven incentives which have, over time, contributed to the development of closed systems. The establishment and propagation of these closed systems of R&D may subsequently lead to stagnation in the 'pipeline' of drug discovery innovation (McKenna, 2014). As a result, innovations that are not inherently profitable are not pursued. Consequently, drug discovery has suffered severe obstacles in the form of knowledge monopolies (Cooke, 2005; McKenna, 2014). The implications of R&D stagnation are significant, particularly with rising concerns regarding viral antibiotic resistance (Willems, 2016) and the emergence of 'superbugs' such as Ebola and Zika (Burke, 2017).

Although academic research is not typically bound by the same profitability constraints, many similar problems have emerged. As previously discussed, Harris (2005) argues that academic researchers are bound by a moral responsibility to societal stakeholders; to produce research that fulfils a societal obligation to innovate. Academic innovation however, may often be stifled by reliance on closed paradigms, and the subsequent 'routinisation' of innovation of the research process (Anderson et al., 2002). Like the case of commercial or private R&D, this routinisation may result in the establishment and propagation of closed models of innovation, effectively constricting the innovation pipeline. This is of particular concern in cases where the convergence of best practice (Kuhn, 1970) and conventional wisdom have become dogmatically ingrained within complex, yet highly inflexible and non-adaptive systems (Cohen, Florida, Randazzesse & Walsh, 1998). In this way, the problem of knowledge aggregation may narrow the focus of some forms of academic research, by introducing boundaries to knowledge aggregation. As a result, innovation is not pursued because it is considered outside the bounds of traditional academic research practice. For Klein (1990), scientific research occurs iteratively in the form of an 'archipelago' of knowledge, where the development of knowledge is often inefficiently duplicated. In this case, knowledge can sometimes be 'lost' to other researchers and practitioners. Often, academic research does not reach practitioners or other researchers at all and instead becomes unused. This is referred to as the 'Death Valley' phenomenon (Kobayashi, Nakamori & Wierzbicki, 2007), and represents another barrier to efficient knowledge aggregation.

In summary, despite significant advancements in the freedom and availability of knowledge, the problem of knowledge aggregation prevents the effective interaction of knowledge inputs. Furthermore, the problem of knowledge aggregation is cumulative in nature. Reliance on closed models of innovation tend to become systematised, to a point where the pursuit of innovation is eschewed, in favour of less risky endeavours. A consideration and discussion of innovation management now follows.

2.3.2 Innovation Management and Breakthroughs

Innovation is the result of the interaction of knowledge inputs (Smith, 2010). Innovation management is defined as the dedicated study of 'breakthroughs' (Smith, 2010). A breakthrough is the outcome of knowledge interactions, that results in a valuable new process, procedure, product or service, that is either entirely novel, or an improvement over its

predecessors (Ahuja & Katila, 2001; Crossan & Apaydin, 2010). In other words, a breakthrough is a radical innovation.

Henderson and Clark's (1990) typology of innovation makes the distinction between incremental and radical innovation, polarised as opposite extremes. Radical innovation is defined as the result of a major technological breakthrough, or the application of new technology (Smith, 2010). According to Henderson & Clark, (1990, p.17), "[r]adical innovation establishes a new dominant design, and hence, a new set of core design concepts embodied in components that are linked together, in a new architecture". According to Smith (2010), radical innovations are generally associated with a high degree of risk and uncertainty, but are also a relatively rare occurrence. In addition, owing to their close association with technological change, radical innovations are often synonymous with 'disruptive technologies' (Christensen, 1997; Christensen, 2013; Christensen, Raynor & MacDonald, 2015). These are technologies associated with significant changes in markets and industries, which often result in high levels of uncertainty and far-reaching consequences (Smith, 2010).

By contrast, incremental innovation involves only modest changes to existing designs (Smith, 2010). More specifically, Christensen (1997, p. 42) defines incremental innovation as "a change that builds on a firm's expertise in component technology within an established architecture". Incremental innovation makes use of existing technology and knowledge, and the expertise associated with it, favouring those with established knowledge and expertise. With an objective of eschewing risk, both commercial, or private R&D and academic research may often favour established knowledge and expertise, over new and untested knowledge and inexperience (Ali, 1994; Norman & Verganti, 2014). As a result, the pursuit of radical innovations is often foregone, in favour of those that are incremental, and therefore, less risky.

Similarly, Linton (2002) differentiates between continuous, discontinuous and dynamically continuous innovations. According to this classification, discontinuous innovations are novel products, processes or services that are so fundamentally different from products that already exist, that they reshape markets and competition. These can be liked to radical innovations and examples include mobile phone technology and the Internet. By contrast, continuous innovations might be liked to incremental innovations. These involve marginal changes to an existing product, without altering customer habits. Dynamically continuous innovations fall

between the two, in that are they may indeed change customer habits but do not introduce discontinuities in markets and industries.

As previously stated, the focus of this research is on the process of academic research. However, most innovation management theory relates primarily to innovation in the context of commercial, or private R&D. It is argued that the fundamental principles that underpin innovation are cross-contextual. In the context of academic research, methodological paradigms are considered tantamount to a technology used in commercial, or private R&D. In other words, methodological paradigms, like technologies, are tools which are used to produce desired outcomes. Thus, in this context, the term innovation is used to refer to methodological change.

In both contexts, innovation occurs in cycles (Smith, 2010). Building on Kondratieff's (1979) theory of long-wave technological cycles, Dosi (1982) puts forth a perspective of technological evolution in the form of a cycle, which is characterised by a series of phases (Anderson & Tushman, 1990). Following the advent of a 'breakthrough', a new technology (or methodology) ushers in an era of flux, in which several forms of the technology exist, and configurations are fluid. Thereafter, through a process of variation, selection and retention (Basalla, 1988), a single design or form of the technology will emerge as the dominant design that becomes an industry standard (Teece, 1986). This process of technological evolution is depicted in Figure 3. The term 'dominant design' is used to describe a configuration that "wins the allegiance of the marketplace" (Nordström & Biström, 2002, p. 713). A dominant design is more likely to be the result of a radical innovation (or, a breakthrough), rather than in an incremental innovation (Teece, 1986). Similarly, Kuhn (1970) suggests that scientific fields undergo periodic paradigm shifts, which may usher in new modes of understanding. Paradigms however, are incommensurable; that is, they are competing and irreconcilable accounts of reality (Baltas, Gavroglu & Kindi, 2000). In this way, parallels can be drawn between methodological advancements (or paradigm shifts) and technological innovation. In both cases, competing modes vie through a process of variation, selection and retention, until a dominant design is established, and the process begins anew.

Foster (1986) introduces the notion of the technology S-Curve, which posits that over time, the capability of a technology to deliver improved performance will vary until the technology invariably reaches a natural limit. Abernathy and Utterback (1978) describe the process of

'punctuated equilibrium' to refer to the manner in which a dominant design (or the introduction of a radical innovation in the form of a major technological or methodological breakthrough) essentially 'punctuates' an existing technological equilibrium, collapsing existing stability to make room for new technologies. These punctuations are discontinuities, which will require new skills, new abilities and new knowledge (Drucker, 1999; Smith, 2010). They are 'competence destroying' and hence, considered very disruptive (Loch & Huberman, 1999). This process is depicted in Figure 3, below.

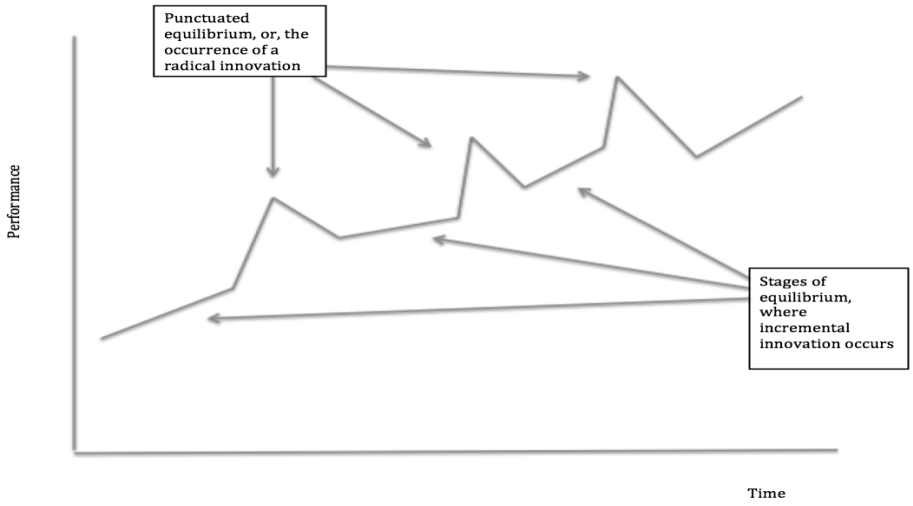


Figure 3: Punctuated equilibrium (adapted from Smith, 2010, p. 77)

In the context of this research, it is argued that academic research is subject to these same principles (Nielsen, 2012). Furthermore, it is argued that the processes associated with closed models of innovation in academic research have, in some instances, reached their natural limit, or S-Curve. Therefore, the obligations of academic researchers to societal stakeholders, may in some cases, not be sufficiently met (Radder, 2010; Fenton, Chillag & Michael, 2015).

Schumpeter (1942, p. 84) refers to 'creative destruction' as the "process of industrial mutation, that incessantly revolutionises the economic structure from within, incessantly destroying the old one, incessantly creating a new one". In this sense, the advent of a radical innovation is the spark that triggers creative destruction. Radical innovations are often disfavoured by organisations because of their 'competence destroying' nature. The advent of a radical innovation is inherently disruptive, and organisations require new skills, knowledge and competencies to survive in these instances (Christensen, 1997; Christensen, 2013; Christensen, Raynor & McDonald, 2015). Despite this, radical innovations are often associated with

positive social externalities (Dismukes, Miller, Bers & Dubrovensky, 2009). Examples include the discovery of X-Rays, vaccinations, penicillin and the iPhone (Bers, et al., 2009). However, radical innovations occur only infrequently. Bers, et al. (2009) refer to Accelerated Radical Innovation (ARI), or the reduction of time that lapses between radical innovations. If ARI can be achieved, then the infrequency and uncertainty surrounding radical innovations could potentially be mitigated. Smith (2010) cites the example of Apple, which introduced radical innovations such as the iPod, iPhone and iPad systematically, over consistently shortened periods of time (2001, 2007 and 2010, respectively). According to Bers, et al. (2009), the attainment of ARI may help be to neutralise the detrimental effects of creative destruction, while simultaneously promoting radical innovation.

Similarly, paradigmatic change in academic research is often met with resistance (Anderson, 1998; Best & Neurhauser, 2004). Some forms of academic research have long been criticised for strict adherence to tradition (Barber, 1961; Herzlinger, 2006; Waring & Bishop, 2010) and inflexibility (Klein & Sorra, 1996). For Kuhn (1970: 2):

> "Science does not develop through the accumulation of individual discoveries and inventions. Scientific progress experiences growing difficulties in distinguishing the 'scientific' component of past observation and belief from what their predecessors had readily labelled 'error' and 'superstition' or 'myths'."

These 'growing difficulties' may be analogous to the notion creative destruction. Paradigmatic change may be met with resistance, because of its competence destroying nature. Like radical innovations, the emergence of new paradigms may be inherently disruptive, and may therefore necessitate new skills, knowledge and competencies. One of the best-known examples of resistance to radical scientific change, is that of Ignaz Semelweiss, who introduced the antiseptic procedure during the 1840's. The procedure was initially rejected in favour of the conventional wisdom of the time, which favoured primitive methods such as 'bloodletting' (Codel, Carter & Barbara, 2005). Eventually, the antiseptic procedure became accepted as best practice but was initially met with powerful resistance. This has been dubbed 'The Semelweiss Effect' (Best & Neurhauser, 2004), which refers to the rejection of change that is contrary to established procedure, despite its' potential to offer superior results. It is argued therefore, that if resistance to paradigmatic, or methodological change in academic research can be overcome, that ARI may become enabled.

Resistance to creative destruction and paradigmatic change is a naturally occurring phenomenon (Schumpeter, 1942; Kuhn, 1970). The evolution of complex systems is often chaotic, until a suitable catalyst intervenes to redirect the process (Nielsen, 2012). However, these forms of resistance represent further obstacles to knowledge aggregation. From the perspectives of both knowledge management and innovation management, there exist substantial barriers to knowledge aggregation, innovation and ARI. It is argued however, that by perforating these boundaries to allow the free and open flow of knowledge, that the process of innovation can be both facilitated and accelerated. It is further argued that the emergence of certain new technologies and methodologies, which offer significant scale advantages, may offer the means to transcend this threshold.

The emergence of new technologies and methodologies (such as the Internet and open innovation, respectively), represents a catalyst that could redirect the innovation cycle, and trigger the commencement of a new generation, or in the words of Schumpter (1942, p. 84); "incessantly destroying the old one, incessantly creating a new one." Rothwell (1994) offers a historical overview of innovation, spanning from post-World War II to the present era, modelled as a typology of industrial innovation. This five-generation (5G) model of innovation, is now discussed.

2.3.3 Rothwell's 5G Model of Innovation

Rothwell's (1994) 5G model structures the chronological progression of industrial innovation. This model typifies past generations of innovation and includes future predictions based on underlying trends. The 5G model is conceptualised in the context of technological advances which impact the innovation process, and which over time, improved production capacities and decreased development costs and times. Although several other notable models of innovation have been composed (Verloop & Wissema, 2004; Jacobs & Snijders, 2008), the 5G mode offers perhaps the most comprehensive overview of process innovation over time (Eveleens, 2010).

Each of the five 'generations' of innovation are alleged to have arisen from distinct business environments that changed over time. The 5G model comprises distinct generations of innovation that each come to existence in response to a significant change in the market. Examples of these changes include economic growth, industrial expansion, more intense

competition, inflation, stagflation, economic recovery, unemployment and resource constraints. The birth of each subsequent generation requires organisations to update their strategic foci, overhaul current innovation processes, and develop new niche markets to remain competitive. For firms caught in the midst of a generation change, technology is the key to adaptation and to addressing environmental threats. However, technology can also pose threats of its own, such as shorter product cycles caused by rapid technological change, which can challenge an organisation's survival (Christensen, 1997; Christensen, Raynor & McDonald, 2015). A constant accumulation of new information is also helpful in addressing these threats. New information can be used to guide decision-making in highly competitive contexts. Technology, however, also offers opportunities. Recent radical improvements in processing power and connectivity that have expanded global economic activity, serve as an example (Dobbs et al.. 2015). Indeed, rapid acceleration of technological advances has become more pronounced since the conception of the 5G model (in 1994). The 5G model is depicted in Table 2, below.

Table 2: Rothwell's 5 Generations of Innovation (Rothwell, 1994)

Generation	Title	Duration
1G	Technology Push	1950s – 1960s
2G	Market Pull	1960s – 1970s
3G	Coupling of R&D and Marketing	1970s – 1980s
4G	Integrated Business Processes	1980s – 1990s
5G	System Integration & Networking	1990s – 2000's

The 5G model proceeds along a U-curve. Each generation is characterised by decreasing time and costs. The most recent (fifth) generation is closest to both the time and cost axes, in development and production processes. This U-Curve is depicted in Figure 4, below.

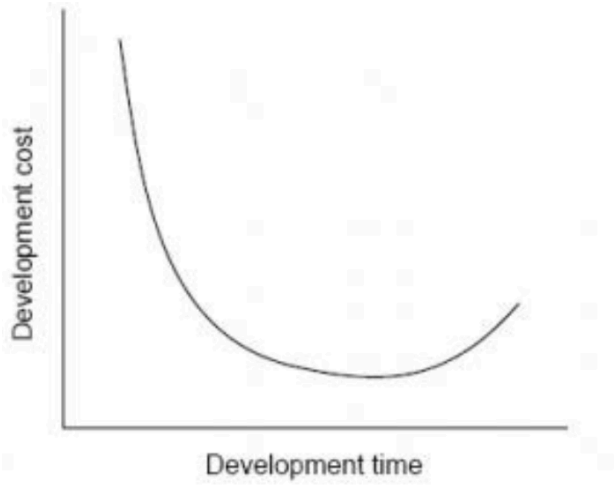


Figure 4: Rothwell's U-Curve (adapted from Rothwell, 1994)

For Rothwell (1994), new generations of innovation arise as a result of increasing complexity and rates of technological change. Christensen (1997) argues that adaptation to change is imperative for firm survival, and that firms that fail to adapt will inevitably demise. As an example, Rothwell (1994) cites the survival requirements for firms that were faced with the shift from the fourth to fifth generation of industrial innovation. These include extensive vertical and horizontal alliances, as well as more flexible and efficient responses to market changes. A historical overview of each of the five generations of industrial innovation now follows. It is stressed that although the 5G model relates primarily to industrial innovation, many of these evolutionary advancements can be paralleled in the context of academic research, which often follows similar patterns (Mansfield, 1991; Mansfield, 1998).

Generation 1: Technology push (1950s-1960s)

Following the conclusion of the Second World War, fast economic growth in the West and Japan led to high levels of demand. This, in turn, allowed for rapid industrial expansion, with an emphasis on supply (a technology 'push'). Organisations primarily focused on research and development, and the generation of scientific breakthroughs. At the core of 1G lay an emphasis on creating new products, as new technological opportunities gave rise to new industries, and technological resurgence in existing industries. R&D funding increased substantially and was considered a fundamental organisational overhead. Consequently, the marketplace was largely ignored. Increases in employment resulted in increased demand and attitudes to science and

technology improved, which was reflected in government policy. There exists a debate as to whether modern organisations should employ technology-push, (1G) or market-pull (2G) methods in their R&D processes (Di Stefano, Gambardella & Verona, 2012). In this context, technology-push refers to organisations pushing for innovation through their own R&D departments, rather than looking to trends in the market. For Nemet (2009), the technology-push model is still suitable in most industries, particularly those funded by government. Indeed, given the exponential rate of technological growth stemming from organisational R&D departments themselves, most modern organisations are more likely to employ a technology push approach (Horbach, Rammer & Rennings, 2012). Examples of modern organisations that make use of technology push approach include Apple and Microsoft (Wonglimpiyarat, 2012). In the context of academic research however, the opposite may hold true. Meyer (2000), for example questions if academic research pushes technology (or paradigms) and concludes that relevancy of the technology in question may be one of the primary motivators of choice of technology push or market pull.

Generation 2: Market pull (1960s – 1970s)

2G innovation was characterised by a race to control market share, inducing organisations to shift their development focus to a 'market pull'. Supply and demand were relatively evenly balanced, but firm focus shifted primarily to demand, rather than supply. The central focus then became responding to the market's needs, rather than pushing new technologies. More stringent resource management became commonplace, as market needs took preference over R&D. The association between R&D and operational units became stronger by including product engineers in scientist-run research teams to decrease time to market. New products were derived primarily from existing technology. As competition increased, strategic emphases moved towards marketing, with the belief that the market was the primary source of ideas for R&D. Unlike 1G, Nemet (2009) notes that 2G-type innovation (or, market-pull) is significantly less suitable than 1G in most modern industries. Indeed, Di Stefano, Gambardella and Verona (2012) suggest that demand-pull models may at times fail to sufficiently address market demand and therefore, that the market-pull approach has decreased in popularity since the 1960s and 1970s. Similarly, in the context of academia, according to Meyer (2000), the difference between technology pull and push is largely dependent on relevancy of the technology (or, paradigm) in question.

Generation 3: Coupling of R&D and marketing (1970s-1980s)

Under pressure from inflation and stagflation, strategic emphasis on consolidation resulted in the rise of 'product portfolios', rather than individual R&D projects. The coupling of R&D and marketing became a critical structural component of the organisation, as a result of the organisational cost reduction imperative. However, conditions of rising structural unemployment led supply to exceed demand. Consequently, the interactions between technological capabilities and market needs became more complex than in previous generations. For example, the Coupling Model emerged as markets and technologies were still sequential, but now had feedback loops to the innovation process through idea generation, research, design and development, prototype production, manufacturing and marketing and sales. These differences (in different sectors), became increasingly pronounced over time, and this model eventually gave way to 4G. In the context of academic research, the coupling of R&D and marketing may be seen to link to Meyers' (2000) notion of project relevancy. Like the differentiation between technology push and market pull, the popularity or widespread usage of certain academic paradigms may be largely dependent on their relevancy to a given academic undertaking. Brusoni, Prencipe and Pavitt (2001) investigate the 'coupling' of different organisational departments (namely, R&D and marketing) in the aircraft engine control system industry and find that the extent of fluidity in organisational boundaries between departments may indeed contribute to a higher level of innovation. In the modern context however, a more integrated business process (4G), particularly one that involves systems integration and networking (5G) is more likely to be successful.

Generation 4: Integrated business processes (1980s-1990s)

With an emphasis on reducing time frames, organisational focus shifted to integrated processes and products. This is referred to as the development of 'total' concepts. Developmental processes became parallel and more closely integrated. Strong external supplier linkages were established, as was close coupling with leading customers. Economic recovery in this period was led by organisations with a focus on core business and technology, and a strategic focus on technological accumulation. Gradually, the importance of manufacturing, manufacturing strategy, alliances and new product life cycles increased. This period was characterised by

functional overlap and intensive information exchange. New imperatives also began to emerge. Examples include environmental imperatives, unemployment and business failures, amongst others. Competition pressures increased, as did the need to accelerate product development. Consequently, quality control became an important component of manufacturing organisations. The notion of integrated business processes applied to the academic research context might be seen as the proliferation of academic collaboration, particularly across departments or across certain fields of study. Following Smith (2010), the interaction of diverse knowledge inputs is expected to result in an increase in the probability of generation innovative outputs. The emergence of new technologies (such as the Internet), however have significantly decreased the access costs to academic collaboration (Sawney, Verona & Prandelli, 2005; Odero & Mutula, 2017).

Generation 5: System integration and networking (1990s-2000s)

The problem of resource constraints became more pronounced during this period. To counteract these constraints, organisational focus shifted towards systems integration and networking. Internally, flexibility and speed of development became important business processes. Some processes became automated, through enterprise resource planning and manufacturing information systems. Externally, focus shifted to business ecosystems, where advanced strategic partnerships and collaborative marketing and research arrangements were fostered. Product values increased in the form of quality and other non-price factors. Rothwell (1994, p. 25) defines 5G as an extension of 4G's parallel and integrated processes. The shift from 4G to 5G occurred as the "technology of technology" began to change, with a new focus on 'lean' innovation. Essentially, 5G reflects a "more comprehensive process of the electronification of innovation, across the whole innovation system." Numerous attempts have been made to expand on the 5G model, since its initial conception (Popov, 2018). Many of these have emphasised recent technological advancements, particularly those associated with knowledge dissemination (Verloop, 2004; Jacobs & Snijders, 2008; Eveleens, 2010).

As previously noted, the progression of industrial innovation and innovation in academic research may share many commonalities (Mansfield, 1991; Mansfield, 1998). The study of technology transfer (from academic to commercial contexts) has provided examples of similar patterns of evolutionary progress (Etzkowitz & Leydesdorff, 2000; Debackere & Veugelers, 2005). Freeman (1995, p. 5), argues that "national and regional systems of innovation remain

an essential domain of economic analysis." In other words, trends in innovation tend to progress in parallel, so long as they are contained within similar economic domains. It is acknowledged that Rothwell's (1994) 5G model of innovation relates primarily to industrial innovation. However, some of the trends and progressions contained in the 5G model may offer useful applications in the investigation of academic research. In turn, findings from an investigation in academic research, may therefore, in some cases, provide insight into similar issues in the commercial, or private R&D context.

This concludes the review of antecedent theory. Building on the 5G model, Callaghan (2014a) suggests that a new 'sixth generation' (6G) of innovation has already emerged. Like previous generations, it is proposed that 6G has emerged as a result of increasing complexity and rapid technological change. Foremost amongst these are the emergence of new technologies and methodologies that may offer significant probabilistic scale advantages. Essentially, 6G theory posits that probabilistic forces can be harnessed to improve innovative productivity. As in the case of previous generational shifts, the emergence of 6G necessitates new skills, knowledge and abilities. In the context of this research, these competencies are referred to under the umbrella term 'technological propensity'. It is also argued that the 6G model offers applications across innovation contexts, including academic research. Sixth generation innovation, probabilistic innovation and technological propensity are now discussed.

2.4 SIXTH GENERATION INNOVATION, PROBABILISTIC INNOVATION AND TECHNOLOGICAL PROPENSITY

In this section, the basis of 6G innovation, as it evolved from the 5G model, is described. This is followed by an account of the theory of probabilistic innovation, which includes discussions on open innovation, crowdsourcing, and crowdfunding. Examples of proof of concept of 6G innovation technologies and methodologies, and probabilistic innovation are also provided and discussed. Finally, the relationship between probabilistic innovation and academic research productivity is delineated.

2.4.1 Beyond 5G: The Emergence of 6G, Real-Time Problem Solving and Social R&D

The application of universal Darwinism to the process of scientific innovation would imply that as innovation evolves over time, it progresses towards a theorised 'perfect state' (Russell,

2015). According to Rothwell (1994), the evolution of innovation, over the course of five generations, has progressively resulted in improved organisational productivity and performance. As markets and economies expand and globalise, organisations adapt, evolve and incorporate the use of new technologies to meet and overcome challenges. As challenges become more complex, they also become more time-sensitive. Organisations that are unable to meet challenges timeously, often fail (Christensen, 1997; Christensen, Raynor & McDonald, 2015). Just-in-time (JIT) production is a methodology aimed primarily at reducing flow times within manufacturing systems (Hirano, 2016). This methodology originated in the 1960's and 70's (during G2 and G3) as a method to reduce time risks associated with automobile manufacturing (Noble, 2017). It became widespread manufacturing practice during the 1980's (G3 and G4). Essentially, JIT is an inventory strategy, that increases efficiency and decreases waste by receiving goods only as they are needed in the production process, thereby reducing inventory costs (Hirano, 2016; Noble, 2017). The success of JIT is purported to have given rise to 'lean' production, which took root during 1990's and 2000's (G4 and G5). For Ries (2011), the lean production method is a systematic method for waste minimisation within a manufacturing system, without sacrificing productivity. Lean production (or, the 'lean method') has become standardised practice across a broad range of industries, from its' initial applications in manufacturing, to hospital management (D'Andreamatteo, Ianni, Lega & Sargiacomo, 2015) and to software development (Svitis, 2015). The scientific method lies at the core of the lean philosophy. Experiments are conducted on a continual basis and the results of each experiment are used as 'experiential learning'. Successful and functional elements of a product or service are sustained and developed, while non-essential components are discarded or changed as required (Ries, 2011).

Similarly, it is argued that if academic researchers are morally obligated to produce innovative research that offers social externalities (Jaffe, 1989; Radder, 2010; Fenton, Chillag & Michael, 2015), then academic research is also constrained by time. In contexts where the loss of human life is at stake (Wu, 2017), it is imperative that innovative solutions are produced as quickly as possible. In this way, academic research may benefit from the application of JIT or lean production methodologies. However, certain alterations to these methods may be required to suit the context of academic research. Again, it is stressed that innovation in different contexts is not identical. However, in some cases, certain parallels may allow for cross-contextual applications.

Callaghan (2017a) argues that if research output is considered in the same terms as industrialised production, and if certain technological advances are applied to the research process itself, then the 5G model can be used as a heuristic description of a new, sixth generation (6G) of innovation. Furthermore, in the 6G model, near real-time productivity is theoretically possible, effectively mitigating the risk of time-bound problem solving. It is argued therefore, that 6G innovation may represent a form of JIT or the lean production methodology, in the context of academic and scientific research. Thus, the application of new technologies to the innovation process may push the U-curve closer to the origin of the time and cost axes. As a result, near real-time research productivity (or, a curve that almost touches the development cost and time axes) may become enabled. The differentiation between the 5G and 6G models of innovation is depicted in Figure 5, below.

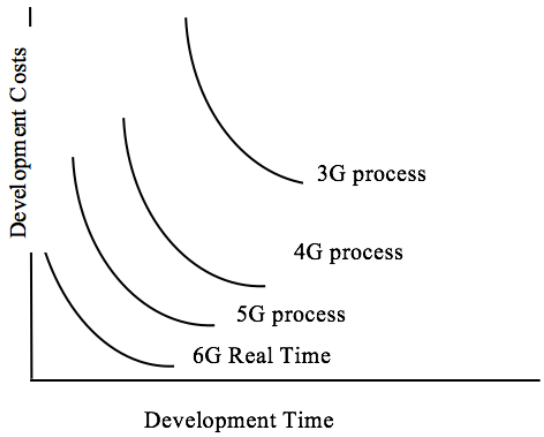


Figure 5: Product Development/Research Production Time/Cost Relationships for 3G, 4G, 5G and 6G Innovation Processes (adapted from Rothwell,1994, p.15 and from Callaghan, 2017b, p. 7)

For Callaghan (2017b), the emergence of certain technological capabilities has enabled new problem-solving potentialities. Real time research productivity might be useful in addressing real-time problems. Examples include the advent of natural disasters, such as hurricanes or earthquakes, or the rapid outbreak of disease. These are problems which occur instantaneously and are notoriously difficult to solve timeously. Real-time research productivity may provide the means to address these problems as they occur, and potentially save human lives in the process. Essentially, 6G mechanisms may offer a way to overcome the problem of knowledge aggregation. Real-time research productivity might be enabled by leveraging the scale

advantages offered by new, large-scale modes of knowledge aggregation, such as crowdsourcing. In this way, the collective knowledge, skills and capabilities of large online communities can be harnessed to orchestrate large-scale research efforts, focused on real-time research capabilities, and specifically geared to producing global social outcomes.

Other similar attempts have been made to expand on the 5G model. For example, Bonney, et al. (2009) suggest that the emergence of certain new mechanisms has enabled increased transparency and accountability of stakeholders in the scientific research process. Despite these advancements and potential applications however, there remains concern regarding the slow rate of global social innovation. For Zoo, de Vries and Lee (2017; p. 334), there exists a "chasm between the industrial and societal goals of innovation." Callaghan (2014a; 2017b) suggests that this gap can be addressed by harnessing newly available technologies and methodologies that fall under a proposed sixth generation of innovation and technology, and which offer real-time problem-solving capabilities. Real-time problem solving may be useful under conditions of societal need, particularly to address global-scale social problems that occur in real time, such as the outbreak of disease. Thus, 6G may represent a paradigm of problem solving that could potentially lessen the gap between the goals of industrial and social R&D.

The shift from 5G to 6G is related primarily to the potential of 'open' systems and processes of innovation, which reduce the knowledge aggregation problem by reducing the 'access costs' of knowledge (Callaghan, 2017b). In open knowledge societies for example, new discoveries are published as soon as they are made (Singh, 2015). Access costs in these societies will be lower than in those where knowledge is kept secret or confined to insiders (Mokyr, 2005). Thus, it can be argued that societies have benefitted from more open access to knowledge (West, Salter, Vanhaverbeke & Chesbrough, 2014). The 6G model may therefore represent a new paradigmatic perspective for engaging with research problems, through the application of probabilistic logic, to radically increase the chance of solving a problem. There exist a plethora of tools and techniques that make use of this probabilistic mechanism. Many of these are already in use have demonstrated significant successes (Howe, 2006; Brabham, 2008; Torr-Brown, 2013). A thorough review of the tenets and principles of 6G, and probabilistic innovation theory now follows.

2.4.2 A Review of 6G Theory: Probabilistic Innovation and the Failure of Innovation

For Callaghan (2014a), the potential of the occurrence of global 'catastrophic events' have become exponentially acute, in the era of globalisation, unprecedented population growth, and mass interconnectivity. In this context, 'catastrophic events' are defined as events that i) occur in real time and ii) hold the potential to inflict social harm, in the form of damage, destruction, and severe loss of human life. Some notable examples include the 2014 outbreak of Ebola, the advent of microbial antibiotic resistance, and the resultant emergence of 'superbugs', as well as the increasing potential for a naturally occurring disasters such as an earthquake or tsunami, as a result of global warming and climate change.

Conversely, the emergence of the radical new technologies, such as the Internet, social networks, and smart-technology have, in the space of a few years, almost instantaneously connected billions of people across the world (Albert, Jeong & Barabasi, 1999; Ziebland & Wyke, 2012). Essentially, these advancements have provided the means to overcome the problem of knowledge aggregation.

A fundamental tension in the literature emerges at this point. Despite significant advances in real-time knowledge aggregation capability, many potentially catastrophic social problems remain unsolved and still pose significant risks to society (Callaghan, 2014c; Zoo, de Vries & Lee, 2017). It has been alleged that the global innovation pipeline, or supply of knowledge that contributes to the erosion of social problems is inherently flawed (McKenna, 2014). It is argued that the failure to adopt new mechanisms, which enable real-time productivity, represents a state of innovation failure. In this context, the term innovation failure is used to refer to a failure to counteract the problem of knowledge aggregation, despite the availability of mechanisms that offer the means to do so (Martin & Scott, 2000; Cutler, 2011). A discussion on innovation failure, firstly in the context of industrial or commercial R&D, and secondly, in the context of academic research, now follows.

2.4.2.1 Innovation Failure: The Case of the Pharmaceutical Industry

Callaghan (2016a) cites the pharmaceutical industry as a prime example of innovation failure. Despite an incentive to produce social outcomes, in the forms of new drugs, treatments and medications, the global pharmaceutical industry has been roundly criticised for its' failure to adequately address the social needs of the global population (Horrobin, 2000; Fenton, Chillag & Michael, 2015). The pharmaceutical industry serves as an example of innovation failure in

the context of industrial or commercial, private R&D. For Callaghan (2015a), this failure stems from a misalignment of incentives. The problem of knowledge aggregation becomes increasingly acute under closed models of knowledge management (West, et al. 2014). Constraints to knowledge flows and interactions effectively cripple the R&D process and ultimately inhibit innovation. In the context of pharmaceutical R&D, investment in innovation is characteristically linked to a profit-driven incentive (Martin & Scott, 2000; McKenna, 2014). Because financial incentives are tethered to the need to generate profitable returns, R&D projects which may offer social externalities, but are not inherently profitable, are not pursued (Martin & Scott, 2000). Consequently, social R&D has suffered significant setbacks. Callaghan (2014a) suggests that pharmaceutical R&D is fundamentally flawed, because it is coupled to the dictates of the market mechanism, which disproportionally allocates resources. For McKenna (2014; p. 2) the gradual decrease in global production and approval of new medications has effectively congested the pharmaceutical innovation pipeline, or supply of new knowledge, which as a result, is "nearly broken". For example, a 2018 study conducted by Goldman Sachs investigated the sustainability of the industry for curable diseases, with an emphasis on once-off cures which may possible through advanced gene editing techniques (Kim, 2018). While these new technologies offer significant value for patients and society, it could represent a challenge for genome drug developers seeking sustained cash flow. The same study cited the example of a new genomic treatment for hepatitis C, which achieved cure rates of more than 90% (Kim, 2018; Vibes, 2018). However, the unmitigated success of the treatment saw profits declining from $12.5 billion to $4 billion in the space of 3 years, essentially "exhaust[ing] the available pool of treatable patients" [Kim, 2018, p. 1].

Another example that points to innovation failure in the case of the pharmaceutical industry is that of 'typically neglected diseases', defined as those that typically affect undeveloped or developing countries, for which cures are possible but have not yet been discovered. For Wu (2017, p. 1), "even with the necessary tools, the world has failed to cure the curable…. Nearly one and half billion people across the world suffer from neglected diseases." It has been estimated that the elimination or controlling of typically neglected diseases could save the world more than $52 billion and over 100 million years of human life, otherwise lost to disease (World Health Organisation, 2015). Despite these pressing concerns, global R&D funding for erectile dysfunction and male pattern baldness outstrips expenditure on typically neglected life-threatening diseases at an estimated rate of 800 to 1 (Wu, 2017). These examples may provide indication as to the extent of innovation failure in the context of the pharmaceutical industry.

Despite the obvious differences between the pharmaceutical industry and academic research, certain similarities may exist. Innovation failure, in the context of academic research, is now discussed.

2.4.2.2 The Routinisation of Academic Research

The term 'academic failure' has been used to describe the market failure of academia to innovate and create new knowledge (Dewald, Thursby & Anderson 1986; Campanario, 2009). For Hanson (1990, p.1):

> Academia is still largely a medieval guild ... Peer review is just another popularity contest, inducing familiar political games; savvy players criticise outsiders, praise insiders, follow the fashions insiders indicate, and avoid subjects between or outside the familiar subjects.

In the context of academic research, Callaghan (2015a, p. 13) suggests that "academic innovation faces a threshold limitation that is inherently related to the academic nature of the R&D process". According to the principle of convergence theory, cultures tend to converge as they progress, eventually homogenising, over time (Robertson, 1992). Academic research may represent a prime example of a culture that has converged on a widely accepted paradigmatic standard. Emphasis on convention and tradition however, may have pushed some forms of academic research to converge on paradigms that are fundamentally fixed, and therefore very difficult to change. This in turn, may result in strict adherence to paradigms that are inherently non-innovative, since innovation is driven by change (Kuhn, 1970; Robertson, 1992). That is not to say that academic research is devoid of innovation. Rather, that strict paradigmatic adherence may, in some cases, be antithetical to the requirements of innovation. This phenomenon is termed academic failure. Unlike innovation failure, which is related primarily to profitability constraints, academic failure relates to the constraints associated with convergence, and inflexible emphasis on convention and tradition. In other words, academic failure is synonymous with a routinisation of the academic process (Anderson, et al., 2004). Like the case of the pharmaceutical industry, this may result in a closed production model, where the flow and interaction of knowledge is constrained, and the innovation pipeline of academic research becomes congested. The previously cited 'Semelweiss Effect' serves as an example of academic failure (Codel, Carter & Barbara, 2005). More recently, attention has been drawn to the system of academic and scientific journal publication. The academic journal

publication system has been accused of being excessively rigid in its' publication criteria. For Campanario (2009, p. 549 - 556):

> "The history of science is dotted with stories documenting how many important discoveries were initially resisted or ignored by fellow scientists... novel theories or discoveries collided with the dominant paradigms in science and were resisted... When this happens, papers are rejected, fellow scientists ignore discoveries, articles are not cited, or commentaries are written against the new finding or discovery… Scientists questioning a widely-accepted paradigm can find it difficult to gain a hearing: questions about fundamentals are rarely welcomed. The instances studied here illustrate that scientists with something truly original to communicate often have to fight against the silence, the lack of interest, and as a result the absence of citations and recognition. Silence and lack of attention is even worse than negative reactions because negative reactions, at least, attract the attention of others who, in turn, might find the new paradigm convincing."

Campanario and Acedo (2007) investigate the initial rejections of what later became highly cited and influential research papers. Campanario (2009) investigates the initial rejection of discoveries made by individuals who would go on to win Nobel Prizes in Physics, Chemistry, Physiology and Medicine. Both of these studies conclude that despite a wealth of documented cases, there seems to have been a relative lack of interest on the part of academics to investigate resistance to scientific discovery. In these contexts, many important discoveries were initially neglected, rejected or ignored. Stent (2002) suggests these discoveries are most likely rejected because they are premature; they do not fit the common paradigm, or their implications cannot be connected to existing scientific knowledge. As a result, radical discoveries are often deemed impractical for some time after their initial communications. Consequently, the pursuit of radically innovative academic research has dampened. Indeed, Alvesson and Sandberg (2013, p. 128) suggest that much present academic research tends to be "specialised, incremental, adding-to-the-literature contributions", which, in turn, "tends to generate a shortage of novel and influential ideas." Like the case of the pharmaceutical industry, these arguments suggest a misalignment of incentives. Journal publications may tend to favour research that is incremental and standardised, over research that tackles important social problems through radical interventions. Goodall (2008) questions the absence research focused on climate change, in highly cited and prestigious management publications. Similarly, Cummings, Morstorf and Zhong (2014) question the surprising dearth of published research on Alzheimer's treatments, despite urgent global need. Begley and Ellis (2012) suggest there

exists a similar paucity of breakthrough cancer treatments, despite significant global support for and interest in oncological research.

The abovementioned examples seem to point to a "routinisation" of some forms of academic research publication. For King and Anderson (2002, p. 327), the content of some of the most influential journal publications have become "less radically innovative… [their] methods increasingly routinised, and predominantly oriented towards field-based, cross-sectional, replication-extensions of previous findings." It is argued that these examples provide evidence of academic failure.

Another potential indicator of academic failure is the peer-review process, which has been described as "a constraint to innovation" (Bornmann, Leydesdorff, & Van den Besselaar, 2010, p. 220). Peer-review lies at the heart of the scientific process; "it is the method by which grants are allocated, papers published, academics promoted, and Nobel Prizes won" (Smith, 2006; p. 178). However, concerns related to the "adequacy and fairness of modern peer-review practices in publication and funding" and about "reliability, accountability, reviewer bias, and competence" have been raised in the past (Peters & Ceci, 1982, p.187). More recently, Smith (2006; p. 178) compares the peer review process with democracy; "a system full of problems, but the least worst we have," but also notes that the peer-review system is "is little better than tossing a coin." Despite the emergence of online, or open access journals, which allow greater accessibility and reach, many of problems related to peer-review seem not to have been alleviated (van Rooyen, Delamothe & Evans, 2010).

Similarly, the peer-review system for grant applications has also been criticised. As universities look to cut costs (Braun & Guston, 2003; Alberts, Kirschner, Tilghman & Varmus, 2014), researcher may be forced to seek external research grants that are allocated through peer review (Bornman et al., 2010). However, similar problems tend to plague the peer-review process for grant applications (Smith, 2006; Alberts, et al., 2014).

For Steinberger (1997, p. 12), "new ideas are not completely easy to accept, sometimes even by the brightest and most open of people." Bornman, et al. (2010) refer to academic reviewers as 'gatekeepers' of science, who recommend for selection the best scientific research under the condition of scarce resources (such as limited space in journals or limited funds). Given the abovementioned examples, which may point to academic failure, it is suggested that a process

of convergence has promulgated a culture of routinisation amongst academic researchers and academic peer reviewers (or 'gatekeepers') alike. Since gatekeepers tend to adhere to stringent, traditional conventions, which tend to favour incremental research over research that is radically innovative, academic researchers tend to produce research that meets these criteria, lest they risk rejection. Consequently, the moral obligation of academic researchers to societal stakeholders may have become compromised. Those academic researchers that do indeed seek to produce academic research, do so at the mercy of innovation gatekeepers. Given the convergence of orthodoxy amongst these gatekeepers, the probability of radically innovative research being funded or published may therefore be low. Callaghan (2015, p. 20179) argues that the cost of non-publication of ideas offering different paradigmatic perspective may be "catastrophic", particularly in the face of potentially disastrous events.

Thus, it is argued that in the context of peer-reviewed academic research, there exists a dearth of radically innovative research that addresses important social problems. Furthermore, that this absence can be traced back to the problem of knowledge aggregation. Obstacles to knowledge aggregation perpetuate closed models of innovation. In closed models of innovation, emphasis on tradition, norms and conventions tend to converge and become routinised. Paradigmatic change is viewed as a risk and is summarily avoided. Incentives become misaligned, and output is dictated by 'gatekeepers', themselves aligned to the closed systems within which they function.

If however, the threshold of knowledge aggregation could be overcome, this may provide grounds upon which more open models of innovation could be fostered. In open models of innovation, paradigmatic change and integration is welcomed, rather than avoided. Consequently, strict emphasis on tradition and convention may become mitigated, and the proliferation of funding and publication of radically innovative, novel research may ensue. An increase in the funding and publication of radically innovative research may, in turn, increase the probability of the funding and publication of research that addresses important social problems, such as the aforementioned climate change and the spread of disease.

In summary, it is argued that the application and implementation of a probabilistic mechanism, inherent to certain new tools, technologies, techniques and methodologies, may offer the means to overcome the problem of knowledge aggregation. This probabilistic mechanism, and probabilistic innovation, is now discussed.

2.4.2.3 The Probabilistic Mechanism and Probabilistic Innovation

Innovation occurs when knowledge interacts (Smith, 2010). But the problem of knowledge aggregation relates to the difficulties associated with precipitating these interactions. The misalignment of incentives (Martin & Scot, 2000; McKenna, 2014) and over-emphasis on routine and standardisation (Anderson, et al. 2004; Campanario, 2009) may further compound the problem of knowledge aggregation. Callaghan (2015a, p. 13) argues that "the only way in which this constraint 'threshold' [of knowledge aggregation] can be breached, consistently is through the adoption of a probabilistic mechanism of knowledge creation."

This probabilistic mechanism is described as the way knowledge and information harness probabilistic forces through the exposure of knowledge to large numbers of people or 'nodes of creation' to find solutions to problems (Callaghan, 2014c; p. 165). It is reasoned that increasing the number of problem solvers would thus exponentially increase problem solutions. This is known as the 'The Law of Reductability', in that the solution to any problem that is ultimately solvable is a function of the quality and quantity of problem-solving inputs it receives. According to Callaghan (2014), the stickiness of knowledge poses a constraint to innovation that cannot be overcome, without the use of a probabilistic mechanism that reconfigures the knowledge space.

The workings of the probabilistic mechanism can be described from the perspective of evolutionary theory, specifically the field of microbiology. To solve newly encountered problems, bacteria assess the problem via collective sensing, recall stored information of past experience, and then execute distributed information processing of the bacteria colony. This essentially transforms the colony into a "super-brain" (Eshel 2009, p. 78). In the case of disease outbreaks, micro-organisms are spread by using a probabilistic mechanism. One infected person will infect two more, those two will each infect another two, and those, another two and so on, increasing the infection rate exponentially. This is a form of distributed learning, or adaptive behaviour and is considered a probabilistic mechanism, which works by harnessing the effects of large numbers (Eshel, 2009). This evolution of micro-organisms runs parallel to the development of new drugs in pharmaceutical R&D in a 'race for survival' (McKenna, 2014; Callaghan, 2015c). The potentially catastrophic effects of micro-organisms learning to outstrip pharmaceutical R&D are evident (So, 2010; Lee & Collins, 2012). Callaghan (2014a) suggests

that the use of a *human* probabilistic mechanism could catalyse exponential human learning, and therefore provide a means to prevent this from happening.

Thus, the term 'probabilistic innovation' is proposed as a new innovation management model (or 'generation), that would theoretically be able to effectively reduce the time and cost dimensions of an R&D, or research project (Callaghan, 2015c). In other words, it would 'crash' the project, almost entirely (Doloi, 2011), allowing for near real-time solutions to pressing social problems. Probabilistic innovation is synonymous with 6G innovation; both entail the harnessing of a human probabilistic mechanism to enhance the rate at which breakthrough innovations are produced. Both are used as terms that refer to a probabilistic paradigm of innovation, knowledge, R&D management and value creation. Thus, if applied to the process of academic research, probabilistic or 6G innovation may enable significant advancements in the production of radically innovative research output. It is stressed that 6G (or probabilistic) innovation is not considered antithetical to traditional modes of R&D or academic research. It is argued instead that innovation is a continuum (Damanpour, 1991), and that the application of certain new 6G innovation processes may provide the means to enhance the rate of breakthrough research productivity. Thus, 6G innovation is not suggested as a replacement paradigm; rather, that 6G innovation may represents a useful complement to contemporary or traditional modes of R&D and academic research productivity.

Nonetheless, it is argued that the application of 6G innovation to the academic research process is essential, given evidence of the routinisation of academic research (Anderson, et al., 2004), the peer-review process (Bornman, et al. 2010), and the academic obligation to innovate (Fenton, Chillag & Michael, 2015). Probabilistic innovation may offer a means to overcome some of the problems associated with these concerns. At its core, 6G innovation theory builds on the theory of open innovation (Chesbrough, 2003a), which is discussed next.

2.4.3 Open Innovation and Open Science

Given the problem of the 'stickiness' of knowledge; von Hippel (1976) argues that users (or end users of a product) play a critical role, not only in generating ideas for innovations, but also in their subsequent development. More recently, von Hippel (2005) describes the democratisation of the innovation process, or the involvement of users as a source of innovation in certain industry sectors. This has become increasingly common in the Information Age,

where new forms of ICT have fostered global communication and collaboration between organisations and the customers (Castells, 2015).

For Chesbrough (2007), a growing division of labour has prompted the need for further democratisation of innovation. Building on Drucker's (1994) 'knowledge economy', open innovation theory posits that a wide and diverse range of knowledge and competencies may exist outside of organisational boundaries. Thus, organisations should strive to develop open business models which leverage synergistic relationships with other firms and individuals (such as product end-users). Essentially, open innovation is a theoretical paradigm of industrial innovation, which refers to "the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation, respectively" (Chesbrough, 2006, p. 2). The open innovation paradigm assumes that adopting an open system of R&D may help to identify, connect to and leverage external sources of knowledge, as a core process of innovation (Chesbrough, 2003a; 2006). For Smith (2010), open innovation is an outcome of an increasingly globalised business environment, where technological advancements have made boundaries between firms and their environments more permeable. Open innovation theory predicts two opposing models of innovation; closed and open, depicted in Figure 6, below.

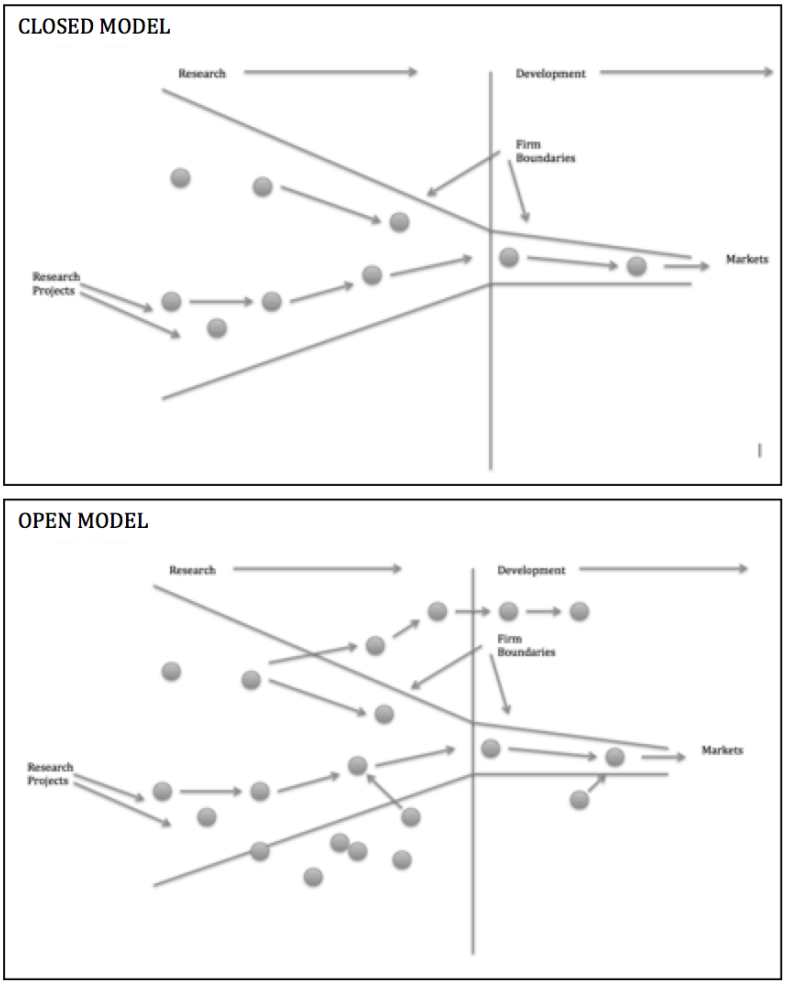


Figure 6: Closed vs. Open Models of Innovation (adapted from Chesbrough, 2003a; p. 36)

In closed models of innovation, firms tend to control and complete the innovation and R&D processes entirely, from idea generation to marketing and distribution, in a funnel approach (Tidd, Pavit & Bessant, 2001). Closed models are not entirely void of flexibility and adaptability. However, these models are often plagued by a high level of value loss stemming from spill-overs (Teece, 1980) and idea project termination (Chesbrough, 2006).

Conversely, open models of innovation draw on external sources of knowledge. Modern innovation processes require firms to master highly specific knowledge about different users, technologies and markets (Kline & Rosenberg, 2010). Those firms that are too internally focused may miss important competitive opportunities (Smith, 2010). As the competitive landscape becomes more complex, an emphasis on external knowledge search has become more commonplace (Laursen & Salter, 2006), rather than an emphasis on continually increasing investments in internal R&D. Whereas traditional approaches to R&D and

innovation face value wastage, open innovation treats spill-overs as an opportunity to expand the organisational business model, or 'spin-off' the technology to a new business model, outside of the firm. (Chesbrough, 2003). For example, firms generally acquire intellectual property (IP) for internal R&D purposes, but patents are for the most part worth very little and often never used (Agrawal & Henderson, 2002; Sawyer, 2009). The open innovation paradigm however, views patents as a new class of asset, which can generate revenue and point to new business. Thus, open innovation theory proposes that firms should be active buyers and sellers of intellectual property (Chesbrough, 2006). A notable example of the successful adoption of an open R&D model is that of Proctor and Gamble. For Brown and Anthony (2011, p. 4):

> At the start of the 2000s only about 15% of P&G's innovations were meeting revenue and profit targets. So the company launched its now well-known Connect + Develop program to bring in outside innovations and built a robust stage-gate process to help manage ideas from inception to launch… A decade later [P&G's] revenues have nearly doubled, helping push annual division revenues from $12 billion to almost $24 billion.

Open source production is a form of open innovation, which leverages communities of product end-users as innovation engines. This mode of production has seen significant growth in the software development industry. In open source production, the essential elements of a certain product are made freely available to users, who can then work collaboratively to improve the existing product. Open-source software (OSS) communities for example, can download source code and then develop it for their own needs (Soderberg, 2015). The modified source code is typically returned for others to develop further. Users often band together, around online discussion forums, to form open source production communities (Lakhani & Wolf, 2003). One of the best known examples of OSS is Linux, a popular, free and open source software that allows users to contribute to and continuously improve on the software's source code (Metz, 2015). The development of Linux employs an iterative process, where users continuously work to change and improve the source code, to better suit their needs (Lin, Hwang & Baker, 2012).

West, Vanhaverbeke and Chesbrough (2006) note that most open innovation studies tend to examine open innovation at the firm level, however neither the practice nor research of open innovation should be limited to the level of the firm. According to West, et al. (2006), the study of open innovation spans multiple levels of analysis, ranging from the individual to the national level. Indeed, the abovementioned examples relate primarily to the firm level, but, the philosophy governing open innovation has also spread to other realms. An example of open

innovation at the level of the individual is that open access journal publications. Open access journal publications have become an increasingly popular mode of research publication for academic researchers. In contrast to traditional scholarly journal publications, open access journals are those that are made available online "without financial, legal, or technical barriers other than those inseparable from gaining access to the Internet itself" (Hodgson, Suber, Kiley, Kaufman, Goodrich & Sutton 2014, p. 1). Although some open access journals charge subscription or publication fees, the majority abide by this description. As of February 2018, the Directory of Open Access Journals (DOAJ) lists over 11000 open access journals, featuring over 2 million articles (Directory of Open Access Journals (DOAJ), 2018).

Fecher and Friesike (2014, p. 10) use the term 'open science' to refer to the application of open innovation philosophy to the scientific process. Thus, open science relates to a scientific culture characterised by its openness, where scientific results are shared almost instantaneously, and with a very large audience. Open science makes use of 'Science 2.0', which is defined as "all scientific culture, including scientific communication, which employs a feature enabled by Web 2.0 and the Internet." Open access journal publication is therefore an example of a Science 2.0 tool, which falls under the open science paradigm.

Notwithstanding these developments, there still exist doubt as to whether academic research has yet fully embraced the open production philosophy (Hey & Payne, 2015; West & Bogers, 2017). Open access journals for example, have been criticised for their perceived low quality (Wicherts, 2016) and 'predatory' tendencies (Shen & Bjork, 2015). Following the definition of open innovation (Chesbrough, 2003a), truly open science would require opening channels of knowledge aggregation, not only to fellow academics, scientists and researchers, but also to those outside the traditional boundaries of academic research; to non-experts, non-scientists and non-academics. Indeed, it has been argued that open access publication has not fulfilled its promise to alleviate the significant barriers to access of scientific knowledge (Suarez & McGlynn, 2017). Despite its perceived advantages to science and society, open access is clearly not freely open to scholars who may often need to pay inordinate fees to publish their results (Suber, 2009). Furthermore, there exist a number of sincere academic integrity concerns regarding scholars paying money to have their work published (Suber, 2009; Pinfield, 2010), especially since most open-access journals are run on a for-profit basis (Fuchs & Sandoval, 2013). Concerns relating to predatory practices of open access publications have also been raised (Bohanon, 2013; Shen & Bjork, 2015). Predatory open access publication refers to an

exploitative business model that involves charging publication fees to authors without providing the editorial and publishing services associated with legitimate publications (Hansson, 2014). Young scholars from developing countries have been found to be especially at risk of being misled by predatory practices (Shen & Bjork, 2015). A number of experiments have been conducted to test the legitimacy of open access publications. In 2013 for example, an experiment submitted a deeply flawed paper on the purported effect of a lichen constituent. Roughly 60% of the open access journals accepted the faked paper (Bohanon, 2013).

These deficiencies of the open access publication system however may represent flaws in the management of open access publication, rather than systemic faults of the nature of open publication itself (Suarez & McGlynn, 2017). Similarly, 'citizen science', also referred to as 'participatory science' is a form of open science, described as "a methodology that enlists the public and in inclusive set of stakeholders in gathering scientific information" (Irwin, 1995 p. 1). In the past, citizen science took the form of 'idea competitions, where citizens (or, non-scientists) are invited to solve problems in exchange for rewards (Stieger, Matzler, & Chatterjee & Ladstaetter-Fussenegger, 2012). A well-known example is the invention of margarine, as an alternative to butter which occurred as the result of a citizen science initiative (Andersen & Williams, 2016). More recently, the emergence of advanced communication tools, such as social media have rapidly increased the use of citizen science. Examples range from amateur astronomy to genealogy to ornithology (Cooper, Shirk & Zuckerberg, 2014), where individuals from across the world supply data, knowledge or information on an open forum for scientific analysis. Like open access journal publication however, citizen science faces limitations. Concerns have been raised about data authenticity and accuracy (Ottinger, 2010). Furthermore, citizen science faces limitations of scale. In the case of time-sensitive research problems, particularly those with societal consequence, it is imperative that solutions are found in as little time as possible.

2.4.4 From Open Innovation to 6G Innovation: Crowds and Collective Intelligence

As defined by Callaghan (2014a), 6G or probabilistic innovation extends open innovation by leveraging external knowledge sources not only from users (von Hippel, 1976), citizens (Irwin, 1995) or from other firms (Chesbrough, 2003), but from the potentially infinite 'crowd' as well (Callaghan, 2014a). For academic research, this would mark a significant departure from traditional modes of knowledge aggregation and research production, but could potentially

provide new modes of knowledge productivity, hitherto unexplored. This mode of knowledge aggregation is referred to as 'crowdsourcing', a portmanteau of the words 'crowd' and 'outsourcing', defined as a distributed problem-solving and production model (Brabham, 2008). For Howe (2006, p. 1), crowdsourcing "represents the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call." Crowdsourcing can take the form of peer-production (when the job is performed collaboratively) but is also often undertaken by sole individuals. The crucial prerequisite is the use of the "open call format and the large network of potential labourers.". Essentially, crowdsourcing is the leveraging of collective intelligence (Brabhamn, 2008).

Collective intelligence is a characteristic of groups of people, which is over and above the individual intelligence of its members (Surowiecki, 2004). Crowdsourcing offers a way to harness collective intelligence. As the world becomes more connected, the potential of collective intelligence grows. The probabilistic mechanism makes use of the 'wisdom of crowds' (Surowiecki, 2004), or the emergent properties of problem solving, which could potentially take form as a function of scale, in the use of crowdsourcing for R&D. This proposed model may prove to be more robust in dealing with the limitations associated with decentralisation and non-transferability of information and knowledge (Hayek, 1945; von Hippel, 1994). According to Callaghan, (2016c, p. 325), "[n]on-probabilistic systems of innovation are less likely to transcend the endogenous limitations of constraints to innovation than are probabilistic systems". For Surowiecki (2004, p. xv):

> If you put together a big enough and diverse enough group of people and ask them to make decisions affecting matters of general interest, that group's decisions will, over time, be intellectually [superior] to the isolated individual, no matter how smart or well-informed he is.

The effectiveness of group-making decisions is widely debated in the literature. Groups have, under some circumstances, shown to have poor judgment; examples include riots or stock market bubbles (Surowiecki, 2004). In these cases, the negative consequences of collectivism and 'groupthink' are clear; the aggregation of group intelligence eventually contributes to entirely irrational and bad decisions. In response, Surowiecki (2004, p. xix) describes the prerequisites for good group decision-making. For a crowd to be wise, "certain prerequisites

exist, namely the need for it to be diverse, to have independence, and to be decentralised." If individuals in the crowd are diverse, they are more likely to think and act independently.

Wooley et al. (2010, p. 687) find evidence of a general collective intelligence factor, the 'c factor', which explains group task performance, defined as "the general ability of the group to perform a wide variety of tasks". This factor is analogous to the 'g factor' (the general intelligence factor of an individual, measured using the same method). Wooley et al. (2010) find that the 'c-factor' is a better predictor of group performance than an average or maximum intelligence level of a collective. Furthermore, Wooley et al. (2010) discover that group cohesion, motivation and satisfaction are not predictors of the c-factor, or the general intelligence level of a collective. This means that scale advantages can be enabled; the larger the collective, the greater the collective intelligence. A more detailed discussion on crowdsourcing and its potential applications now follows.

2.4.5 Crowdsourcing

Crowdsourcing is the leveraging of collective intelligence (Brabham, 2010). Crowdsourcing is differentiated from citizen science, in that it relies on the cumulative input of large numbers of people, both expert and non-expert, rather than individual strands of input from non-experts (or, citizens). Furthermore, crowdsourcing is differentiated from other forms of open innovation or open science, in that it is typically "internet-mediated" (Bartling & Friesike, p. 336). Crowdsourcing typically involves three key players: i) the project initiator (or requester), who seeks information, data or the solution to a problem, ii) the crowd-workers, who offer their services in the form of problem, knowledge, data or information and iii) the platform provider, who links the requester with the crowd-workers (Renwick & Mossialos, 2017). These intermediary platforms are most often web-based and designed specifically to leverage the scale advantages associated with large numbers of people. In some cases, crowdsourcing can occur without a requester, or project initiator and involves only the interactions of crowd-workers on a crowdsourcing platform. One of the best-known examples of this model is Wikipedia, a free, online and crowdsourced encyclopaedia. Wikipedia has seen significant growth and success since its inception, and has been described as "the most comprehensive, representative, and pervasive participatory platform for knowledge production ever created by humankind" (Adler, De Alfaro, Mola-Velasco, Rosso & West, 2011, p. 11).

Given its reliance on the Internet, the use of crowdsourcing has flourished in today's postmodern society (Goneos-Malka, Grobler & Strasheim, 2013). Advances such as Web 2.0 technologies, social networks and other similar advancements have enabled the real-time connectivity required to make crowdsourcing work effectively (Stieger et al., 2012). It has been argued that the emergence of crowdsourcing has precipitated further advancements in 'knowledge economics' (Drucker, 1994; Howe, 2006), also referred to in this context as 'wikinomics' (Tapscott & Williams, 2006). The success of Wikipedia is perhaps the most well-known example of the success of the crowdsourcing model, where "hobbyists, part-timers and dabblers suddenly have a market for their efforts [for] smart companies in industries as disparate as pharmaceuticals and television" (Howe, 2006, p. 2). Other popular web-based platforms such as YouTube crowdsource user-generated content in the form of video footage, while some more recent applications crowdsource services, such physical transport (e.g. Uber).

Crowdsourcing has however come under notable criticism (Holloway, Bozicevic & Borner, 2007; Kostakis, 2010; Christensen, 2015). Wikipedia for example has been criticized for the factual reliability of its content (Niederer & van Dijck, 2010), systemic biases (Reagle & Rhue, 2011) and editorial vandalism (Heindorf, Potthast, Stein & Engels, 2015). For Black (2010: 1), the content of most Wikipedia articles can be described as "truth, half-truth and some falsehoods". Wikipedia does however acknowledge these faults and accedes that information on Wikipedia should not be used as a primary source for research, either academic or informal (Solorzano, 2013). Nevertheless, the high level of accuracy attained in certain areas may provide indication as to usefulness of large online collectives, under certain conditions.

The success of crowdsourcing is driven by its facilitation of diffusion (von Hippel, 2005). Where previously tacit knowledge, as a resource, was scarce (von Hippel, 1976), global adoption of the Internet and related communication tools has created an open pool of potential labourers or problem solvers, who work collaboratively to accurately pinpoint ideal solutions to problems, for extremely low cost (Brabham, 2008). In this way, the resource costs of knowledge search and knowledge management has decreased dramatically (Kittur, Chi & Suh, 2008). For Howe (2006, p. 1), "distributed labour networks are [now] using the Internet to exploit the spare processing power of millions of human brains" (Howe, 2006, p. 1). Numerous online crowdsourcing platforms have emerged as a marketplace for solution seekers and problem solvers to interact (Brabham, 2013).

InnoCentive is one such platform, which through 'commission-based R&D, allows organisations to pose 'challenge problems' for anyone to solve. Cash prizes are awarded to the best solutions (Lakhani & Panetta, 2007). InnoCentive's open model has proven to be considerably successful at problem-solving and has been "found to be associated with the ability to attract specialised solvers with range of diverse scientific interests." (Lakhani & Panetta, 2007, p. 103). Furthermore, successful solvers solved problems at the boundary or outside of their fields of expertise, indicating a transfer of knowledge from one field to others (Afuah & Tucci, 2012).

Amazon's Mechanical Turk (MTurk) is an online crowdsourcing platform that enables individuals or businesses to coordinate the use of human intelligence to perform tasks that computers are currently unable to perform (Brabham, 2008). Requesters are able to post jobs known as Human Intelligence Tasks (HITs), such as "choosing the best among several photographs of a storefront, writing product descriptions, or identifying performers on music CDs" (Corney, Lynn, Torres, Di Majo, Regli, Forbes & Tobin, 2010, p. 574). Workers (or crowd-workers) can then browse among existing jobs and complete them in exchange for monetary payment set by the requester.

The use of crowdsourcing has expanded significantly in recent years. Wikipedia, InnoCentive and MTurk are perhaps the most well-renown examples of online crowdsourcing platforms but numerous other platforms have sprung up to meet significantly increased demand (Paolacci, Chandler & Iperiotis, 2010) and in some cases, to create demand that did not previously exist (Kohler, 2015). Crowdsourcing is increasingly adopted by large organisations looking to reduce costs associated with R&D (Kohler, 2015). Callaghan (2014b, p.1505) refers to 'crowdsourced R&D' as "a methodology, or a set of methods used to generate knowledge or source large data inputs that addresses the problem of knowledge aggregation". According to this definition, crowdsourced R&D can be leveraged by organisations seeking to reduce R&D expenditure, by harnessing scale advantages offered by large collectives. Callaghan (2015a) suggests that crowdsourced R&D is a methodology that is particularly well-suited to health, medical and biomedical R&D. Indeed, there exist numerous proof-of-concept examples of the use of crowdsourcing for data collection, analysis and clinical trials (Torr-Brown, 2013). Proteomics, or the study of large-scale proteins has become increasingly important in the identification and development of new drugs for the treatment of disease (Barsnes & Martens, 2013). Because proteomics is an exceedingly complex field and requires substantial knowledge

inputs from a diverse range of expertise, distributed knowledge networks (i.e. crowdsourcing) has been used to significant effect to analyse mass data generated from proteomics research (Verhuggen, Barsnes & Martens, 2014). Several online platforms, such as BioMart (Guberman, et al., 2011) have been established as intermediaries for this process. Further examples include the use of crowdsourcing networks for HIV-AIDS and cancer research (Torr-Brown, 2013). Some forms of medical research have also been known to make use of a process known as gamification, or the use of game thinking and game mechanics in non-game contexts to find innovative solutions to problems (Huotari & Hamari, 2012), which is then outsourced to the crowd. A University of Washington experiment called *FoldIt* asked users to try 'solve the puzzle' of folding various protein structures (relating to AIDS research) using video-game tools and mechanics. In contrast to scientific researchers that had been working on similar problems for extended periods of time, solutions sourced from the crowd (players) were reached in just three weeks (Torr-Brown, 2013).

Crowdsourcing platforms, such as MTurk have also been increasingly used for social science research. Despite concerns regarding validity and the potential for fraudulent data (Caslet, et al, 2013), MTurk has been described as a "highly valuable opportunity for data collection" (Goodman et al., 2013, p 213). MTurk has mostly been shown to produce similar results to those of traditional sampling in behavioural research, "with MTurk participants being significantly more socio-economically and ethnically diverse, yet … test results … were indistinguishable" (Casler, et al., 2013, p. 2156) from traditional sampling methods. Bahrend, Sharek, Meade & Wiebe, (2011) investigate the use of crowdsourcing research participants for organisational psychology research, finding that crowdsourcing respondents tend to be older, more ethnically diverse, and have more work experience than traditional university participant pools. Furthermore, the reliability of data from crowdsourcing samples tends to be as good, or better than corresponding university samples. Measurement invariance generally held across these groups. Shank (2016) investigates the viability of crowdsourcing sociology research participants using MTurk and finds similar results.

Aside from survey data collection however, other forms of crowdsourcing are rarely used in academic research, and perhaps rightfully so. Wikipedia has been criticised for its perceived failure as a reliable source. Wikipedia editors may have little expertise, competence or credentials in the topics to which they contribute (Maehre, 2009). However, a series of studies which compared Wikipedia articles on pathology, toxicology, pharmaceuticals and psychiatry

to peer-reviewed articles, found that Wikipedia's depth and coverage were of a high standard. For example, articles about pharmacology, were found to maintain 99.7% accuracy rate when compared to peer-reviewed journal articles (Kräenbring et al., 2014). More recently, academic researchers have begun to accept Wikipedia as a "valuable starting point" (Maggio et al., 2017, p. 165), both for student education and academic research itself. Another more recent study reports that the odds of an open access journal being referenced on Wikipedia are 47% higher than for 'pay-walled' journals and suggests that this constitutes a significant amplifier effect for science published on open, or crowdsourced platforms (Teplitskiy, Lu & Duede, 2017).

These examples show the scope of crowdsourcing potential. Some of the most pressing concerns regarding the use of these techniques relates to the privacy (Kajino, Arai & Kashima, 2014), reliability (Varshney, 2012) and security (Yang, Zhang, Ren & Shen, 2015) of crowdsourced participants. Certain regulations and legislation that protects the right of crowd-workers and prevents fraud and exploitation have been developed and instituted (Brabham, 2013). Chandler, Paolacci and Mueller (2013) assess the risks of certain crowdsourcing marketplaces and offer a set of guidelines about how to ameliorate these issues through task design, workforce selection, data cleaning and aggregation.

Despite its potential the use of crowdsourcing does face a number of limitations. Chief amongst these are ethical limitations (Heymann, 2014). Durward, Blohm and Leimeister, (2016) investigate the ethical issues associated with crowdsourcing by following the PAPA (privacy, accuracy, property and accessibility of information) and find that although there are indeed PAPA dimensions in crowdsourcing, only few focus on the crowd-workers as individuals. Although crowd-workers may not feel exploited (Busarovs, 2011), crowdsourcing may still be considered an exploitative practice, "since seven out of sixteen definitions of exploitation describe crowdsourcing as exploitation (Durward, Blohm & Leimeister, 2016, p. 829). Moreover, the use of crowdsourcing to solve problems or to complete certain tasks also faces the risk of inaccurate input from malicious crowd-workers (Gadiraju, Kawase, Dietze & Demartini, 2015). This can shave significantly negative consequences for work being sourced to crowds. However, Wang, Huang and Louis (2013) suggests that fair compensation may be key to alleviating malicious intent of this nature.

However, these risks may, in some cases, not need be addressed. Some of the risks associated with crowdsourcing, particularly those related to misinformation and human error, may be

‘cancelled out’ as they occur. Indeed, as previously discussed, despite its obvious shortfalls Wikipedia has, in some cases, a significantly high rate of accuracy, in some examples as high as 99.7% (Kränenbring, et al., 2014). This may be attributable to the nature of large collectives, which essentially manage themselves without needing a centralised authority.

Callaghan (2015c) refers to Adam Smith’s (1776) ‘invisible hand’ hypothesis and its relationship to efficient markets to explain how crowds engages in brokerage or trade of knowledge to solve price problems in the market. The use of crowdsourced R&D may provide similar conditions to the mechanisms of a market, since crowds also work in systems to solve problems. The theoretical foundation of 6G is underpinned by collective intelligence. Systems that exhibit chaotic dynamics at the individual level have been found to sometimes have stable conditions at the collective level. Essentially, the collective intelligence of a crowd might be viewed as analogous to the qualities of other complex systems, such as the human brain, complex ecological systems and financial markets (Teece, 1986; Yong, 2013). Studies in swarm intelligence, or the intelligence of ‘social insects’ have described the phenomenon known as stigmergy, which may help to describe the underlying ‘invisible hand’ hypothesised by Adam Smith (1776).

Stigmergy is defined as the achievement of complex coordination without a central decision-making capacity, occurring commonly in natural systems such as flocks of birds and ant colonies (Garnier, Gautrais, Theraluz, 2007). Through stigmergy, task decomposition is possible. Task decomposition may be highly suited to humans who are highly specialised at performing certain tasks or have certain specialised knowledge.

Research on stigmergy provides anecdotal evidence of methods through which the abovementioned concerns are addressed due to the inherent nature of crowd behaviour (Callaghan, 2015c) in that crowds tend behave like social insects (Suroweicki, 2004, Yong 2013). According to Garnier, et al. (2007) the example of ant colonies explains how contextual triggers push each individual in the crowd to respond with an individual specialised input, effectively providing a space in which problems can be solved in real-time (as they occur). The mechanisms of the crowd can be compared to the example of ant colonies, which can solve difficult problems to obtain food or build nests through self-organised cooperation. Using pheromones to communicate, changes by one insect in the swarm can trigger changes in the other insects to achieve perfect cooperation and synchronisation. This is the process of

stigmergy (Garnier et al., 2007). Similarly, crowd-workers shift between roles based on a flexible and adaptable crowd-work algorithm based on stigmergy. In this way, the crowd solves the problem 'piece-meal' through unique cues to each individual at certain times and certain places. Essentially, individual crowd-workers populate the problem space, filling it with their own specialised knowledge until the problem is solved (Callaghan, 2016c). Crowd-level problem solving, however, is not structured; it is possible that complex adaptive systems may explain Adam Smith's 'Invisible Hand' hypothesis (Kochugivonda &Vriend, 1998). Workers in the crowd do not need full information on the problem, rather only to maximise their own utility, using their own specialised skills and knowledge (Surowiecki, 2004; Callaghan, 2015c). A 'market' of problem solutions takes shape around the problem space; one in which an open exchange of knowledge, ideas and problem-solving inputs takes place until the entire problem is eroded. Studies in group behaviour have uncovered a certain set of dynamics that, when applied, create order from chaos (Derényi &Vicsek, 1995). Seemingly complex behaviour often has simple foundations, based on 'if-then rules', which, when applied, can relate to the way swarms of insects and flocks of birds form, and how cancer cells spread (Yong, 2013)

Essentially, a swarm is a 'hive mind' and functions similarly to the motion of neurons in the human brain, which fire in favour of different options (e.g. go right or go left), ultimately culminating in a decision. The same has been found to occur in the formation of tumourous cancer cells (Yong, 2013). It is argued that the emergence of the Internet has unlocked the inherent potential of humanity to act as a highly efficient and effective swarm, rather than as individual components or teams. For Torr-Brown (2013, p. 2), "scientific progress is likely to occur through networks of human intelligence that can frame and solve difficult problems but are also supported by supercomputing capabilities". Crowdsourced R&D may therefore offer the potential for multi-disciplinary problem solving using distributed knowledge systems, essentially solving the problem of knowledge aggregation, by making specialised skills and knowledge readily available. Many of the principles and theory that underpins crowdsourcing also apply to its financial counterpart, crowdfunding, which is discussed next.

2.4.6 Crowdfunding

Crowdfunding is defined as "an Internet-based mechanism through which individuals solicit small amounts from many donors instead of a single large sum from an institution" (Averett, 2013, p. 908). It can also be defined as a mechanism of external financing (Torr-Brown, 2013).

One of the best-known crowdfunding platforms is 'KickStarter,' a web-based platform which allows users to pose project ideas and allows other users to fund these projects by contributing small amounts of money, until a total monetary objective is attained, and the project is fully funded (Averett, 2013). 'Backers' (those who fund projects) are offered rewards in exchange for their donations and contributions (Walker, 2017). Kickstarter however, accounts for only a small percentage of the total crowdfunding industry, which has grown exponentially in recent years (Roberts, 2017). In 2013, the crowdfunding industry raised a total of US $6.1 billion dollars. It expanded by 167% in 2014 to US $16.2 billion and then more than doubled again to US $34.4 billion in 2015 (Salmann, 2016). The World Bank estimates that crowdfunding will surpass US $90 billion by 2020 (Barnett, 2015). In comparison, the venture capital (VC) industry presently invests an average of US $30 billion a year (Barnett, 2015), whereas angel capital averages roughly US $20 billion a year (Barnett, 2015). The increased popularity of crowdfunding is expected to contribute significantly to economic growth, innovation and job creation (Thompson, 2014). The use of crowdfunding has been cited as a promising advancement in developing countries, where "85% of [people in developing countries] have mobile phones, with a growing share of 'smart phones' that can enable crowdfunding in its different forms" (Thompson, 2014, p. 407).

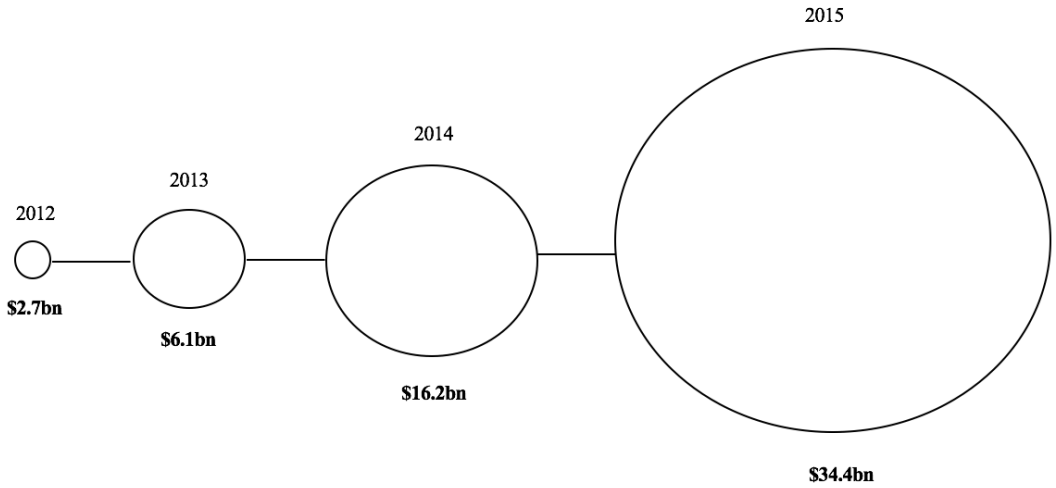


Figure 7: Growth of the crowdfunding industry 2013 – 2015 (adapted from Massolution, 2015, p. 1)

Crowdfunding has been used to fund a wide range of for-profit, entrepreneurial ventures, such as artistic and creative projects (Belleflamme, Lambert & Schwienbacher, 2014). However,

much of its use has also shifted to community-oriented, social entrepreneurship projects, such as covering the cost of medical expenses or aggregating charitable donations (Feller, Gleasure & Treacy, 2016). Crowdfunding has been suggested as a feasible solution for the issue of funding in medical research (Torr-Brown, 2013; Palmer & Verhoeven, 2017; Roberts, 2017), which is often heavily constrained by regulatory hurdles (Stewart, et al. 2015). Indeed, the use of crowdfunding to finance medical research has become increasingly common (Moran, 2017).

Dragojlovic and Lynd (2014) investigate the use of crowdfunding to raise funds for oncological research (including basic research, drug discovery and clinical trials) and ultra-rare diseases and conclude that crowdfunding may indeed offer a viable approach to supporting some forms of medical research. Renwick and Mossialos (2017) suggest that crowdfunding in the health market presents unique economic applications, but has been inadequately explored, thus far.

Nevertheless, Drogjlovic and Lynd (2017) argue that there is an emerging trend for health scientists to directly crowdfund donations for their not-for-profit research work. For example, GoFundMe, one of the largest donation-based crowdfunding forums in the world, raised US $147 million for medically-related projects in 2014, up from US $6 million in 2012 (Cunha, 2015). Their health section for donations is the platform's most popular category and generated 26% of all donations in 2014. Oncology research has been one of the major foci for crowdfunding efforts, with a number of platforms dedicated to cancer-specific crowdfunding (Renwick and Mossialos, 2017). Crowdfunding has also been used to generate funding for rare diseases research, which is often neglected by traditional financing sources (Wu, 2017). For Dragojlovic and Lynd (2017, p. 17):

> Crowdfunding may help pull money into these unique funding gaps. A 2016 Pew Research Centre survey found that 84% of donors believe that crowdfunding "highlights causes or businesses that might not get much attention otherwise." For instance, GoFundMe's largest campaign to date raised more than USD $2 307 million from over 37,000 donors around the world to support a young girl with a very rare neurological condition. Additionally, crowdfunding may fill holes in health research agendas by funding niche or high-risk health science fields. There is building evidence to suggest that crowdfunding may be an effective method for bringing scientists and donors together to finance early stage clinical trials targeting rare and neglected diseases. Crowdfunding proof-of-concept research and initial clinical trials could allow scientists to attain more substantial grant funding or entice private investment.

Pharmaceutical and biotech SMEs as well as spin-off companies from university research groups are using platforms such as Crowdcube and ShareIn to sell equity stakes in their company in return for capital (Fiminska, 2015). This money may be used to accelerate clinical testing and development of a novel therapy, expand health service offerings, or scale up production and operations for a medical product (Dragojlovic & Lynd, 2014; 2017)

Despite its success and global adoption, crowdfunding seems not to have yet become commonplace in the funding of academic research. Traditionally, the main source of funding for university research comes from either private or government grants (Mazzucato, 2015). Grant schemes are often highly competitive with low success rates, favour experienced or senior researchers, and take considerable time to be processed, thereby delaying potential discoveries (Palmer & Verhoeven, 2016). For Roberts (2017: 17) "the time is now ripe for university management… to embrace new technology platforms as part of their strategic finance planning to take advantage of new emerging revenue models in combination with existing operations". In 2015, an experiment at the Australian Deakins University successfully raised over AUS$185,000 for 19 different research projects by crowdfunding alone (Palmer & Verhoeven, 2016).

Crowdfunding can be viewed as the monetisation of one's social capital (Hui, Gerber & Greenberg, 2012), depending largely on online social communities. Social media activity (such as the use of Twitter and Facebook) has been shown to be critical to crowdfunding success (Palmer & Verhoeven, 2015). For the academic researcher looking to crowdfund their research, it is critical that they "build their 'audience' to interact with and build their academic 'brand'" (Roberts, 2017: 18), using multiple social media channels to create interest and develop potential funders. Presently, there exists a number of platforms that provide guidance to academics on how to connect with a wider audience. SciFundChallenge is a web-based platform that provides educational tools for academic researchers looking to crowdfund their work. Content dissemination providers to the academic sector like Knowledge Unlatched, are also exponents of the crowdfunding model, combining it with open access and working directly with libraries and publishers (Roberts, 2017).

The use of crowdfunding does pose some potential drawbacks. Dragojlovic and Lyn (2017) highlight five potential economic risks which may arise from crowdfunding health projects including i) inefficient priority setting, ii) financial risks, iii) unclear regulatory frameworks,

iv) issues of accountability, transparency and due diligence and v) risk of fraud. It is also important to note that not all crowdfunding campaigns are successful. Between 2011 and 2013, it was reported that 1 in 5 crowdfunding initiatives failed in the United Kingdom often due to a lack of interest from potential 'backers', although poor management and insufficient support also contributed to these failures (Salmann, 2016). These issues are especially pertinent if crowdfunding is to be adopted in the academic research. Indeed, they may be the reason crowdfunding for academic research has not yet become commonplace practice, outside of the health research initiatives described above.

Notwithstanding these issues, crowdfunding may indeed offer new opportunities for academic researchers looking outside of the traditional channels of research funding (Roberts, 2017). However, crowdfunding has yet to be fully embraced by academic researchers, despite the notoriously difficult and bureaucratic procedures usually associated with research funding (Rubinton, 2011; Palmer & Verhoeven, 2017).

Given the literature reviewed above, it is argued that a model that comprises of both crowdsourcing and crowdfunding may provide the necessary grounds to break through some of the constraints associated with routinisation and conformance in academic research. Commenting on the use of crowdfunding in health research, Debelius, et al., (2016) note that "crowdfunding, alongside crowdsourcing, has supported valuable scientific breakthroughs." Callaghan (2015b) describes three different 6G innovation models, which combine crowdsourcing and crowdfunding as a way to maximally harness the probabilistic forces of both. These models are discussed next.

2.4.7 Callaghan's Models of 6G: A Combination of Crowdsourcing and Crowdfunding

Crowdsourcing may hold significant potential to support knowledge aggregation and problem solving. Crowdfunding has emerged as a viable alternative to traditional funding methods. The use of both crowdsourcing and crowdfunding have gained exponential traction in recent years, in response to significant technological advancements, particularly the Internet. Despite their flaws, both may be viable candidates for use in academic research, which may often be constrained by paradigmatic conformance or regulatory hurdles. Both may offer significant scale advantages over traditional modes of knowledge or fund aggregation. Both fall under the 'Open Science' paradigm (Fecher & Frieske, 2014), and both fall under the proposed 6G

innovation paradigm (Callaghan, 2014a). Most importantly, both crowdsourcing and crowdfunding can be harnessed to find solutions to problems in *real-time*. This bears significant consequence for academic research that seeks to address problems that impact societal stakeholders. Thus, Callaghan (2014; 2015; 2016; 2017) suggests that a 6G model is one that combines the simultaneous use of crowdsourcing and crowdfunding. The application of a 6G model to the research process may enable exponential scale advantages, effectively increasing the probability of problem-solving exponentially, and dramatically decreasing the resource, time and cost constraints usually associated with problem solving. The types of 6G models are described. These include i) The Global Model, ii) The Synthesis Model and iii) The Nexus Model. Each of these are briefly discussed.

For Callaghan (2014a; p. 2078) the 'Global Model' incorporates the use of crowdsourcing to direct knowledge inputs, and crowdfunding to direct financial inputs towards solving global problems. "If countries were to pledge certain future health budget costs, then a cumulative 'reward fund' could be pooled that was large enough to enable crowdsourced R&D to find solutions." As per the Law of Reductability, certain new technologies and methodologies associated with the 6G paradigm of innovation may hold the potential to increase the odds of problem solving. The Global Model predicts that the solution to a problem is a function of the quality and quantity of solving the inputs it receives. However, this logic will only apply to problems that are inherently solvable. For example, applying to 6G theory to solve the problem of time-travel would prove impossible. Finding a cure to a disease however, is inherently possible, despite the many difficulties associated with finding such a solution.

Callaghan (2015a, p. 21) extends the Global Model into a 'Synthesis Model', which "can account for its own genesis". The Synthesis Model is a theorised prototype which combines the use of both crowdsourcing and crowdfunding, to seed and sustain itself. The Synthesis Model is social, rather than proprietary because of the 'multiplier effect'; feedback flows transcend dyadic mechanisms typically used in traditional models, and knowledge and funding gets fed back into the crowd (or the model itself). The Synthesis Model differs from the Global Model in that it can 'seed' itself, by harnessing the probabilistic forces inherent to crowdsourcing and crowdfunding. Knowledge and funds are leveraged through the crowd to increase the chances of success, or the probability of finding a solution. In this way, problem solving is spread across a large number of potential solvers and funders. 'Learning' in the form of knowledge is fed back into the system (the crowd) for further feedback. Funding in the form

of small monetary contributions are fed back into the system (the crowd) so that model is sustained.

The Synthesis Model is differentiated from traditional models of research or R&D, which are fundamentally dyadic in nature. Conversely, 6G models of innovation (such as the Synthesis Model) are inherently multi-directional and have infinite feedback loops synchronised to work until the system itself reaches a 'perfect' state. In addition to its multi-directional nature, 6G innovation also makes use of the 'multiplier effect', which draws from epidemiological theory. The multiplier effect relates the exponential spread of knowledge in a similar fashion to the exponential spread of viruses; one person infects two people, these two people infect a further four people, these four people then infect a further sixteen, and so on. In the case of knowledge dissemination, the multiplier effect allows for learning and problem solving to increase exponentially and instantaneously (in real time). The result is non-proprietary, multidirectional flows of shared information, with no need to keep the information secret. Therefore, information is fed back into the crowd, generating accelerated, real time, exponential learning, knowledge creation, innovation and problem solving. Moreover, Callaghan (2015a) argues that this model is better suited to solving social problems that are outside the ambit of market incentives, rather than those models which are tethered to the need to generate revenue.

Research shows that even small incentives can augment motivation to crowd-work (Harrison, 2013). Incentives themselves can be crowdfunded, as a certain percentage of all funds raised. To this end, the Synthesis Model would i) incorporate the use of crowdfunding (Harrison, 2013), ii) generate resources followed by crowdsourcing (Howe, 2006), and iii) generate knowledge, information and solutions to problems. According to Callaghan (2014a, p. 2074) the self-sufficient nature of such a system "might be appropriate for a wider and more diverse range of interest groups because of these advantages". Thus, while the Synthesis Model may be scale dependent, it can potentially be applied on a large scale to solve global problems with world-wide impact, or can equally be applied to smaller, more localised problems. Once again, it is stressed that 6G, probabilistic innovation is not proposed as a replacement to current and longstanding paradigms, technologies and methodologies. Rather it is presented as a set of complementary methodologies, best suited to situations where it is not profitable to pursue a solution to a given problem.

The Nexus Model seeks to find the 'locale' or 'space' which exists at the nexus of social 6G and proprietary 6G, where incentives are aligned (Callaghan, 2016a). One potential way to align incentives is the use of online innovation contests (Hallerstede & Bullinger, 2010). However, according to Chesbrough (2003a) while open innovation can accelerate innovation, it does not address the problem of the difference between social and proprietary innovation. However, the Nexus Model may be able to address this overlap by creating a space that can vastly accelerate the probability of successful problem solving, or the generation of breakthrough innovations. It is at this point that a critical mass might be reached, where incentives are aligned with societal goals. On the basis of these three models, Callaghan (2016a) offers three propositions, as follows:

- **Proposition 1**: The higher the financial incentives provided for social probabilistic R&D, the higher will be the overlap of intrinsic and extrinsic motivation on the part of contributors.
- **Proposition 2:** The higher the financial incentives provided for social probabilistic R&D, the greater the areas of overlap between social and proprietary R&D in their problem-solving efforts.
- **Proposition 3:** Using 6G R&D, almost any problem can be solved. The only constraints being i) the size of the financial incentives, ii) the extent to which the problem is solvable, and iii) the time it might take.

On the basis of these propositions it is argued that any problem that is a function of knowledge (and is therefore inherently solvable) can be solved relatively quickly, so long as sufficient financial resources are invested in the process. Furthermore, medical and biological problems might be uniquely suited to this paradigm of problem solving, because such problems are 'finite systems', which means that they are inherently knowable and therefore, if enough resources are applied, are ultimately solvable.

Following Foster (1986), innovation failure stems from prior generations of innovation reaching the natural limit of their S-Curves, resulting in declining returns on investments. In some industries however, incentives are often misaligned to profitable, rather than social outcomes (martin & Scott, 2000). In cases such as these (for example, the pharmaceutical

industry), the pursuit of profit may trump the pursuit of innovation, leading to innovation failure (King & Anderson, 2004).

Thus, 6G may represents a new S-curve which according to Foster (1986) and Christensen (1997), organisations should seek to adopt immediately, less they risk losing competitive advantage. Productivity in the academic research context is not constrained by profitability, but as previously discussed, may be constrained by adherence to certain fixed paradigms of knowledge creation and fund aggregation (Anderson, et al., 2002; Hanson, 2000; Campanario, 2009). Technologies and methodologies associated with 6G have already emerged. Callaghan (2016a) argues that the scale of these interventions needs to be ramped up so that the nexus of social and proprietary R&D can be created and the rate of problem solving increased exponentially. Similarly, in the context of this research, it is argued that some forms of academic research have reached their natural S-limit, and may be misaligned to routinised incentives, rather than socially beneficial outcomes. It is also stressed that breaching the limits of routinisation, does not imply a breach in the quality standards of academic research. Furthermore, it is argued that by harnessing certain probabilistic modes of productivity, that a nexus of social and academically viable academic research can be created, and the rate of breakthrough research productivity increased exponentially.

This research seeks to investigate the extent of individual academic researchers are willing to engage with and adopt certain new modes of productivity which may enable scale advantages. This willingness, or propensity is likened to the absorptive capacity, or "the ability to recognise the value of new information, assimilate it and apply it to commercial ends" (Cohen & Levinthal, 1990, p. 128) of a firm. For the purpose of this research, this measure of individual-level absorptive capacity is referred to simply as 'technological propensity'.

2.4.8 Technological Propensity

In the context of this research, the term 'technological propensity' is used to refer to the extent to which individuals seize or take advantage of certain new scalable technologies and methodologies (such as crowdsourcing and crowdfunding), to enhance productivity. In other words, technological propensity refers to the absorptive capacity of an individual.

Cohen and Levninthal (1990, p. 128) define absorptive capacity as "the ability to recognise the value of new information, assimilate it and apply it to commercial ends" as a function of previously related knowledge. Thus, individuals with higher technological propensities are more likely to recognise the potential (or value) of certain new scalable modes of productivity and are therefore more likely to adopt them in the hope of enhancing productivity. Technological propensity is also then a function of prior knowledge; individuals who are in possession of 'previously related knowledge' (i.e. knowledge of other, non-scalable modes of productivity) may be more likely to recognise the value of new scalable modes of productivity.

Innovation theory predicts that the diffusion of innovation is often dependent on individual-level adoption (Greenhalgh, Robert, Macfarlane, Bate & Kyriakidou, 2004; Smith, 2010). Rogers (1995) differentiates between individual innovation adoption categories, emphasising the importance of innovators and early adopters in the diffusion of the innovation process. Innovators and early adopters are characterised as risk takers, opinion leaders and social leaders (Greenhalgh, et al., 2004). In the context of this research, innovators and early adopters would be expected to have high levels of technological propensity. Being innovative (Rogers, 1995; Greenhalgh, et al., 2004), such individuals may also be more likely to produce breakthroughs.

Thus, in the context of this research, technological propensity refers to the extent to which individuals exhibit the characteristics of innovators and early adopters, in terms of certain new scalable modes of productivity such as crowdsourcing and crowdfunding. Technological propensity represents a measurement of behaviour related to the adoption of new and untested tools, techniques, methods and technologies to improve productivity, and a measurement of value recognition.

6G theory predicts that the adoption of certain new modes of productivity may enhance productivity. Given the definition of technological propensity, and in the context of 6G theory, it is argued that technological propensity is positively associated with productivity. Individuals with high levels of technological propensity may produce more than those with low levels of technological propensity. However, given the constraints associated with academic routinisation (Anderson, et al., 2002), it is also acknowledged that technological propensity may in some cases, be negatively associated with productivity. If routinised academic systems, secured and promulgated by innovation gatekeepers (Bornman, et al. 2010) reject unconventional modes of productivity, then the adoption of new, unconventional modes of

productivity may also be met with resistance. In this case, high levels of technological propensity may be associated with lower levels of productivity. The extent of the relationship between technological propensity and productivity therefore depends on the extent of routinisation in a given academic research system (e.g. journal publication or academic research funding). An overview of 6G theory is provided in the table below.

Table 3: Overview of 6G Theory

Overview 6G Theory			
		Theory	**Key Theorist(s)**
1	**Antecedent Theory**		
1.1		The Evolution of Knowledge	Gray (2009) Scwhab (2016) Rothwell (1994) Callaghan (2014, 2015, 2016, 2017)
1.2		Innovation Management and Breakthroughs	Christensen (1997) Henderson & Clark (1990) Schumpeter (1942) Christensen, Raynor & McDonald, 2015
1.3		Knowledge Management and the Problem of Knowledge Aggregation	Drucker (1987, 1994) Nonaka (1994) Hayek (1945) Von Hippel (1976)
1.4		Rothwell's (1994) Model of 5G Innovation	Rothwell (1994)
2	**The 6G Model**		
2.1		6G: The Probabilistic Mechanism	Callaghan (2014, 2015, 2016, 2017)
2.2		Open Innovation	Chesbrough (2003a, 2007)
2.3		Crowdsourcing	Howe (2006) Brabham (2008)
2.4		The Wisdom of Crowds and Collective Intelligence	Surowiecki (2004) Wooley, et al. (2010)
2.5		Swarm Intelligence and Stigmergy	Garnier, et al. (2007) Rosenberg (2016)
2.6		Crowdfunding	Brabham (2008)

Overview 6G Theory			
2.7		6G Models (Global, Synthesis, Nexus)	Callaghan (2014, 2015, 2016, 2017)
2.8		Technological propensity	Cohen &Levinthal (1990) Rogers (1995)

The discussion of 6G theory is now concluded. The relationship between technological propensity and productivity is now further delineated. A consideration of some of the potential determinants of research productivity now follows, as does the derivation of propositions.

2.5 THE DETERMINANTS OF RESEARCH PRODUCTIVITY AND HYPOTHESIS DERIVATION

This research seeks to investigate the relationship between technological propensity and productivity, in the context of academic research. There exists a gap in the literature as to the use of crowdsourcing, crowdfunding and other similar modes of productivity (i.e. 6G innovation) in the broad context of academic research, and the relationship between the uptake of these methodologies and productivity. It is this gap that this research hopes to address. This research is conducted at the level of the individual. Thus, individual-level differentiators, which may impact the relationship between technological propensity and productivity, must also be considered. This section is structured as follows. First, a discussion of the dependent variable, productivity is provided. Thereafter, discussions of various individual-level differentiators which may impact the relationship between technological propensity and productivity are discussed. There are referred to under the umbrella term Human Resources (HR) determinants and relate to unique, individual-level differences in behavioural orientations and motivational configurations. These determinants are considered important in the investigation of the relationship between technological propensity and productivity because they are proximal to the individual. In other words, they may help to provide a clear indication as to the different influences that affect the relationship in question and that may vary from person to person. The HR determinants used in this study include i) personality, ii) motivational values, iii) work climate perceptions and iv) human capital investments. Differences in 'field of study' and gender are also considered. Productivity is discussed next, as follows.

2.5.1 Productivity

For Altbach (2015, p. 1) "the measurement of academic productivity is neither straightforward nor easy". Most commonly, a total number of publications per researcher over time is used as the standard measurement protocol in discerning research productivity (Abramo, D'Angelo & Di Costa, 2014). However, the extent to which a journal publication can be considered innovative (or a 'breakthrough') is debatable (Ahuja, & Katila, 2001, Srivastava & Gnyawali, 2011).

In the context of this research, productivity refers to output over time. This research seeks to investigate the relationship between technological propensity and productivity across three separate points on a spectrum of productivity, including: i) crowd-work productivity, ii) academic research productivity (referred to simply as 'productivity') and iii) breakthrough research productivity (BRP). Crowd-work productivity refers to the rate of completion of crowd-work tasks over time. Academic productivity refers to the rate of publication of academic journal articles over time. BRP refers to the extreme end of the productivity spectrum and involves the production of radically innovative, breakthrough scientific or academic research.

The relationship between technological propensity and academic research productivity is the focal point of this research. According to literature discussed above, academic research may in some cases be constrained by routinisation (Anderson, et al, 2004), where over-emphasis on tradition, standardisation and paradigmatic conformity may inhibit the radical innovativeness (or breakthrough potential) of academic research output. However, 6G innovation theory offers a new perspective on knowledge creation, where by harnessing collective intelligence of large collectives, such as online crowds, scale advantages might be enabled. In this way, the probability of finding solutions to problems may increase exponentially. Similarly, it is argued that if the logic underlying 6G innovation were to be applied to the context of academic research, that the constraints associated with routinisation and standardisation might be overcome. Thus the relationship between technological propensity and productivity is investigated in three different contexts. Firstly, in the context of academic researchers, to assess the viability of 6G innovation in the context of academic research. Secondly, in the context of crowd-workers, to investigate the mechanisms of crowd-work productivity in the 6G 'space'. Thirdly, in the context of breakthrough producers, or those individuals who have produced

notable radically innovative breakthroughs, to investigate the drivers of BRP and how 6G innovation might contribute towards the production of breakthroughs. The objective of investigating productivity across these three levels is therefore to draw a holistic synthesis of the drivers of BRP and to investigate the extent to which 6G innovation is indeed applicable and valuable to the academic research process. As previously discussed, the term technological propensity is used to refer to the individual-level inclination to seize opportunities associated with certain new modes of productivity (such as crowdsourcing or crowdfunding), which may offer significant economies of scale. Here, Hypothesis A1 is introduced:

HA1: technological propensity is significantly associated with productivity

It is stressed that technological propensity is not a simple, broad measure of innovativeness. In the context of this research, technological propensity is specific to the extent to which individual take advantage of certain new modes of productivity associated with scalable methodologies such as crowdsourcing and crowdfunding. Measures of technological propensity and innovativeness are therefore not the same but do share similarities. Both technological propensity and innovativeness are related to an underlying adoption of and engagement with novel ideas, processes and techniques. The relationship between individual-level innovation and productivity has been investigated extensively (West & Farr, 1990; West, 2002; Link, Siegel & Bozeman, 2007; Bozeman, Fay & Slade, 2013). In the context of workplace innovation, King and Anderson (2002) list i) knowledge, ii) skills and iii) other aspects (referred to collectively as KSOAs) as the foremost indicators of innovative behaviour and productivity. KSOAs can be measured at three levels of analysis including the individual, work-group and organisational levels. Numerous studies have shown that at each of these levels, a number of factors exist that can both impede and support innovative outcomes (Sun & Wang, 2006; Hunter, Cushenbery & Friedrich, 2012; Wang & Zatzick, 2015); however, these factors vary widely according to context. Given the similarities between measurements of technological propensity and innovativeness, it is argued that both measures may share common facilitators (i.e. KSOAs). For the purpose of this research, only the individual-level factors are considered, since this study investigates the innovativeness of individuals, rather than work-groups or organisations. At the individual level, King and Anderson (2002) list four interlinking facilitators of innovative performance, depicted in Table 4, below.

Table 4: Facilitators of innovative performance at the individual level of analysis (adapted from King & Anderson, 2002, p. 151).

	Facilitator	Factors
1	**Personality**	Tolerance of ambiguity, self-confidence, openness to experience, unconventionality, originality, rule governed, authoritarianism, independence, and proactivity.
2	**Motivation**	Intrinsic vs. extrinsic, determination to succeed, and personal initiative.
3	**Job characteristics**	Autonomy, job demands, span of control, job dissatisfaction, support for innovation, mentor guiding, and appropriate training.
4	**Cognitive ability**	The 'g' factor – above average intellect, task specific knowledge, divergent thinking style, and ideational fluency.

Each of these above-mentioned facilitators is now discussed in detail, including personality, motivation (referred to as 'motivational values') and job characteristics ('referred to as work climate perception'). Cognitive ability is not discussed further as it is beyond the scope of this research. Instead, Human Capital Investments (HCI) is considered as an additional potential facilitator of innovative performance. Personality is discussed first, as follows.

2.5.2 Personality

Personality is defined in terms of "the physical, mental, moral and social qualities of the individual" (McKenna & Bargh, 2000, p. 11) and can be understood as a complex of characteristic features describing the dimensions through which personalities are categorised (Thompson & McHugh, 2009). Others have defined personality as "the set of psychological traits and mechanisms within the individual that are organised and relatively enduring and that influence his or her interactions with, and adaptations to, the intra-psychic, physical and social environments" (Larsen & Buss, 2010, p. 4). These 'psychological traits' are often defined as a bundle of personality attributes, commonly referred to as the Five Factor Model (or FFM) of personality (also known as the 'Big Five' model) (Costa & McRae, 1995). Empirical research has shown that the 'Big Five' model is able to account for different personality traits, without overlapping (Boyle, 2008). The model is also considered trans-theoretical in nature (Costa & McCrae, 1990). Costa and McCrae (1989) refer to the Five Factor Model of personality as a hierarchical organisation of personality traits, applicable across observers and cultures (see Table 5 below). All five factors have been shown to have convergent and discriminating validity (Costa & McCrae, 1990). According to Costa & McCrae, (1989, p. 177)

> [T]he FFM provides a common language for psychologists from different traditions, a basic phenomenon for personality theorists to explain, a natural framework for organising research, and a guide to the comprehensive assessment of individuals that should be of value to education, industrial/organisational and clinical psychologists.

Table 5 below lists each of the five personality traits of the FFM model, which includes Neuroticism (N), Agreeableness (A) Continuousness (C), Openness to Experience (O) and Extraversion (E) (Costa & McRae, 1995; Goldberg, 1981; McCrae & John, 1992).

5: Examples of Adjectives, Q-Sort Items, and Questionnaire Scales Defining the Five Factors of Personality (adapted from Costa & McCrae, 1995, p.178)

Factor (Personality Trait)	Adjectives (a)*	Q-Sort Items (b)*	Scales (c)*
Extraversion (E)	Active, Assertive, Enthusiastic, Energetic, Outgoing, Talkative	Talkative, skilled in play, humour, rapid personal tempo, facial gestures expressive, behaves assertively, gregarious	Warmth, gregariousness, assertiveness, activity, excitement seeking, positive emotions
Agreeableness (A)	Appreciative, Forgiving, Generous, Kind, Sympathetic, Trusting	Not critical or sceptical, behaves in a giving way, sympathetic, considerate, arouses liking, warm, compassionate, basically trustful	Trust, straightforwardness, altruism, compliance, modesty, tender-mindedness
Conscientiousness (C)	Efficient, Organised, a Planner, Reliable, Responsible, Thorough	Dependable, responsible, productive, able to delay gratification, not self-indulgent, behaves ethically, has high aspiration level	Competence, order, dutifulness, achievement striving, self-discipline, deliberation
Neuroticism (N)	Anxious, Self-Pitying, Tense, Touchy, Unstable, Worrying	Thin skinned, brittle ego defence, self-defeating, basically anxious, concerned with adequacy, fluctuating moods	Anxiety, hostility, depression, self-consciousness, impulsiveness, vulnerability
Openness (O)	Artistic, Curious, Imaginative, Insightful, Original, Wide Interests	Wide range of interests, introspective, unusual thought process, values intellectual matters, judges	Fantasy, aesthetics, feelings, actions, ideas, values

		in unconventional terms, aesthetically reactive	

(a) Adjective checklist items defining the factor in a study of 280 men and women rated psychologists serving as observers during an assessment weekend at the Institute of Personality Assessment and Research (McCrae & John, 1992).

(b) California Q-Set items from self-sorts by 403 men and women in the Baltimore Longitudinal Study of Aging (McCrae, Costa & Busch, 1986)

(c) Revised NEO Personality Inventory facet scales from self-reports by 1539 adult men and women (Costa, McCrae & Dye, 1991)

Each of the five personality traits listed below contain two separate but correlated aspects as a part of the model (DeYoung, Quilty & Petersen, 2007). These facets are included in parentheses next to each broad title.

2.5.2.1 Extraversion (E) (Enthusiasm and Assertiveness)

Extraversion describes individuals who are outgoing, energetic, sociable and assertive, and is related to energy gleaned from external means (Atkinson, 2014). Watson and Clark (1984) identify seven components of Extraversion (or 'E') including venturesomeness, affiliation, positive affectivity, energy, ascendance and ambition. Like the other four factors of personality, extraversion varies along a spectrum, with one extreme being individuals who are outgoing, assertive or energetic and the other being individuals who are solitary or reserved (Costa & McCrae, 1989). Extraverted individuals tend to seek stimulation in the company of others and are generally talkative and action-oriented. However, highly extraverted individuals may also tend to be attention-seeking and domineering individuals (Costa & McCrae, 1990). Conversely, individuals with low extraversion scores tend to be reserved, reflective, aloof and self-absorbed (Costa & McCrae, 1989). Such individuals are commonly referred to as 'introverts', who require less stimulation and social interaction than extraverts (Costa & McCrae, 1989).

2.5.2.2 Agreeableness (A) (Compassion and Politeness)

Agreeableness (or 'A') is the tendency to be compassionate and cooperative, rather than suspicious and antagonistic towards others (Costa & McCrae, 1990). Agreeableness is related to "more humane aspects of humanity … characteristics such as altruism, nurture[ing], caring and emotional support at one end … hostility, indifference to others, self-centeredness, spitefulness and jealousy at the other" (Digman, 1990, p. 422). Those with a high degree of agreeableness tend to be friendly, kind, compassionate, cooperative, trusting and trustworthy. Such individuals are generally optimistic about social harmony and are willing to compromise

(Costa & McCrae, 1992). However, extremely high agreeableness is sometimes associated with naivety or submissiveness (Costa & McCrae, 1989). Disagreeable individuals, however, are generally associated with character traits such as suspicion and skepticism, and tend to be argumentative, competitive and less likely to be cooperative (McCrae & Costa, 1989). Agreeableness has been shown to correlate positively with the quality of relationships with other team or group members (Barrick, Stewart, Neubert & Mount, 1998), an important indicator of ability to work in a team.

2.5.2.3 Conscientiousness (C) (Industriousness and Orderliness)

Costa and McCrae (1990, p. 197) describe Conscientiousness (or 'C') as a combination of "a dimension that holds impulsive behaviour in check" and that also "a dimension that organises and directs behaviour". Conscientiousness is associated with the manner in which people control, regulate and direct their impulses (Costa & McCrae, 1992). A conscientious individual is expected to be efficient, organised, dependable, self-disciplined and a planner. Conscientiousness can be seen to link closely to performance (Costa & McCrae, 1992) and is commonly associated with individuals that aim for achievement, are dutiful and are inclined to prefer planned, rather than spontaneous behaviour (McCrae & Costa, 1989). High levels of conscientiousness can result in individuals being viewed as stubborn or obsessive, while low conscientiousness indicates flexibility and spontaneity, which can however, sometimes also be perceived as unreliability (Costa & McCrae, 1992).

2.5.2.4 Neuroticism (N) (Volatility and Withdrawal)

Neuroticism (or 'N') "represents individual differences in the tendency to experience distress (and generally unpleasant emotions), and in the cognitive and behavioural styles that follow from this tendency" (McCrae, & Costa, 1989, p. 195). Neuroticism is also commonly referred to as 'emotional instability' and is linked closely to low tolerance for stress or aversive stimuli (Eysenck, 1967). Respondents with a high N score (those with sensitive or nervous personality characteristics) are prone to recurrent nervousness, frustration, guilt, depression, sensitivity, self-consciousness and vulnerability (Atkinson, Nolen-Hoeksema, Fredrickson, Loftus, & Lutz, 2014; McCrae & Costa, 1989). These attributes often associate closely with low self-esteem, irrational decision-making, and poor control or coping skills (McCrae & Costa, 1989), which often results in a pessimistic approach to work and personal relationships. On the other

hand, respondents with low N scores (those with secure or confident personality characteristics) are generally associated with calmness, and being less emotionally reactive (McCrae & Costa, 1989), although this can also indicate lack of inspiration or unconcern.

2.5.2.5 Openness to Experience (O) (Intellect and Openness)

For Costa and McCrae (1990, p. 198), openness to experience (or 'O') "includes aspects of 'Intellect' but is considerably broader in scope". Openness to experience is comprised of personality traits such as inventiveness and curiousness and is said to reflect the degree of individual-level intellectual curiosity, creativity, independence, imaginativeness and a preference of variety and novelty (Atkinson, et al., 2014). Openness to experience can also be described as an appreciation for experience, related to those who are intellectually curious, open to emotion and sensitive to beauty and the pursuit of self-actualisation. These items are however, not mutually exclusive (Costa & McCrae, 1990). Open traits can often be perceived as unpredictable or lacking in focus. Open individuals have also been noted to have a propensity to use symbols and abstractions in their thinking processes. Individuals who score lower on the openness scale tend to have more concrete, conventional thinking facilities and may be resistant to change (Barrick, et al., 1998). Interestingly, Specht, Egloff and Schmukle (2011, p. 6) find that "the development of openness has shown a curvilinear pattern, increasing in early adulthood and decreasing in old age." Costa and McCrae (1990) note that individuals with lower levels of openness to experience tend to follow conventional ways of thinking and in some cases, may also be more risk averse than others (Barrick et al., 1998).

King and Anderson (2002) argue that personality is a facilitator of innovation. In the context of this research, technological propensity represents a measure of individual's willingness to explore unconventional (or 'innovative') modes of productivity. Thus, personality may be related to technological propensity. Since different personality types impact innovative behaviour and productivity in different ways (Rushton, et al., 1981; Feist, 1998; Cubel, et al. 2016), personality might also mediate the relationship between technological propensity and productivity. Here, Hypotheses A2 and A5 are introduced, as follows:

> *HA2: Personality is related to technological propensity*
> *HA5: Personality mediates the relationship between technological propensity and productivity.*

Several previous studies have assessed the FFM in academic researcher samples. Rushton et al. (1981) assess the association between personality and academic research productivity, finding that academic researchers' productivity may be associated with conscientiousness and openness to experience. Conversely, academic research productivity may be negatively associated with extraversion and agreeableness. Interestingly, academic researchers often tend to exhibit traits that relate to neuroticism more than comparative populations. Feist (1998, p. 290) investigates the association between personality and 'scientific creativity' amongst academic researchers. In this context, scientific creativity is defined as "creative thought or behaviour that is novel, original, useful and adaptive." The measurement of scientific creativity may provide a useful heuristic description for the measurement of technological propensity, since both measures account for a 'uniqueness', an open orientation and a willingness and inherent ability to 'think outside the box', despite pressure to conform to traditions. Feist (1998) concludes that conscientiousness and openness to experience are strongly associated with scientific creativity, while extraversion, agreeableness and neuroticism negatively associated with scientific creativity. Similar associations might be expected between technological propensity and personality. More recently, Cubel et al. (2016), investigates the association between personality and productivity amongst scientists and academic researchers. Again, conscientiousness is found to be strongly associated with research productivity, while neuroticism is found to be negatively associated with research productivity. Ozer and Benet-Martinez (2006) suggest that the Five Factor Model of personality may act as an accurate predictor of performance outcomes. However, this view has been met with criticism. For Murphy (2007, p. 685)

> The problem with personality tests is … that the validity of personality measures as predictors of job performance is often disappointingly low. The argument for using personality tests to predict performance does not strike me as convincing in the first place.

The FFM model has been found to maintain consistency across a wide range of participants, of different ages and cultures in the literature (McCrae, 2001). Despite this, the model has been subject to considerable critical scrutiny (Jakobwitz & Egan, 2006). Some have suggested that the model is limited in its capacity as an explanatory or predictive mechanism (Costa & McCrae, 1995) and that the five traits associated with the FFM model do not account for the

'abnormal personality trait sphere' (McCrae, 2001). Despite the critiques of the Five Factor Model, these five dimensions of personality aptly describe the broad categorisations of individual personalities for the purposes of this research. Most importantly, the FFM is considered a useful and proximal psychological measurement that differentiates individuals, and therefore may links closely to individual-level technological propensity. Measurement of individual personality may then provide for an accurate indication of the ability and willingness to adopt a certain new, unconventional modes of productivity. Motivational values are discussed next.

2.5.3 Motivational values

For Hancock (1992, p. 7) motivation is "the mainspring of behaviour; it explains why individuals choose to expend a degree of effort towards achieving particular goals." In organisational theory, one of the principal concerns is "to increase motivation in the search for greater productivity" (Thompson & McHugh, 2009, p. 307). In the context of this research, the term motivation is the theoretical construct used to explain research behaviours (Tremblay, Blanchard, Peltier, Taylor & Villeneuve, 2009). However, simple consideration of intrinsic and extrinsic motivations may not suffice in fully delineating the relationship between technological propensity and productivity. To this end, it is argued that motivational *values* (Schwartz, 1992, 2007, 2012) may provide clearer indication of the individual-level variance in the relationship under investigation. While the use of the FFM model may be a comprehensive measurement of traits, it may not hold the potential to account for intrinsic biological, social and psychological needs. Schwartz (1992) offers a formulation of motivational values which take these needs into account and may help to further differentiate individuals.

According to Schwartz (2012), values are crucial for explaining social and personal organisation and change. They are used to characterise cultural groups, society and individuals, to trace change and to explain the motivational base for attitudes and behaviour (Rokeach, 1973). Schwartz's (1992, 2007, 2012) values theory focuses on universal applicability; it identifies ten motivationally distinct types of values and specifies the dynamic relations among them. Values are structured in similar ways across culturally diverse groups, which suggest that there may be a universal organisation of human motivations (Rokeach, 1973; Schwartz, 1992). It must be noted that different individuals and groups, however, may have different

value ‘priorities’ or ‘hierarchies’ of values, which differentiates them from others. For Schwartz, (2012, p. 3), motivational values theory six features, or characteristics, which are common across all contexts. These include the following:

- Values are beliefs, linked inextricably to affect.
- Values refer to desirable goals that motivate action.
- Values transcend specific actions and situations.
- Values serve as standards or criteria.
- Values are ordered by importance.
- The relative importance of multiple values guide action: trade-off.

Motivational values can be categorised into ten dimensions, according to the motivation that underlies each of them. Schwartz (2012) theorises that the reason for the seemingly universal nature of values theory can be attributed to the fact that the values model is grounded in three universal requirements of human existence; namely, biological, social, and survival/welfare needs. These are translated into goals and values, as socially desirable concepts. According to Schwartz (2012), motivational values can be further grouped into four ‘higher-order motivational values. Each of the lower and higher order motivational values are depicted in Figure 8, below.

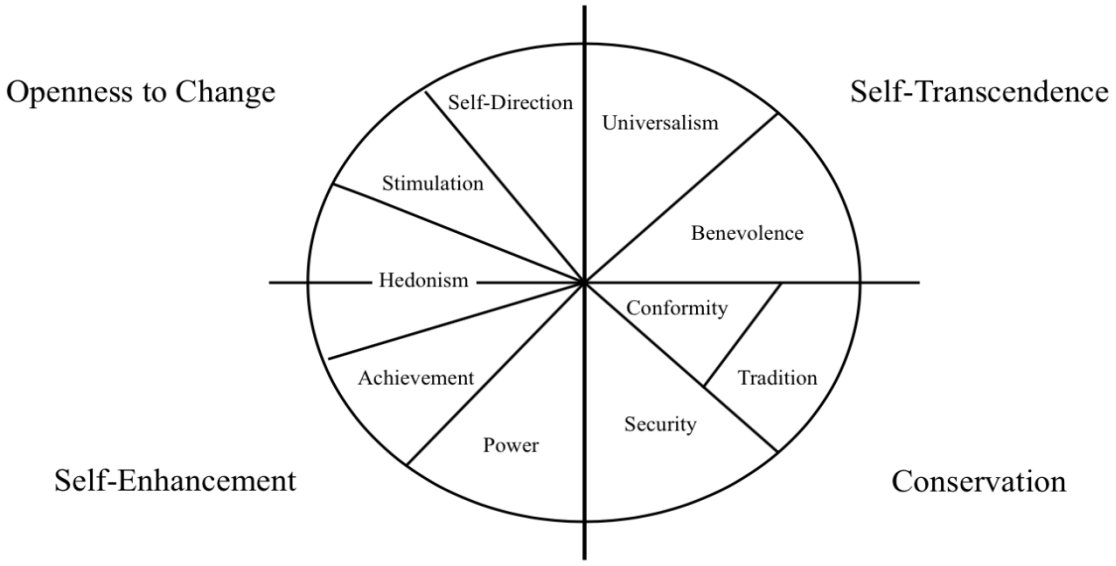


Figure 8: Schwartz's Values Model (adapted from Schwartz, 2012, p. 9)

The following discussion is structured according to Figure 8 (above), starting from openness to change and proceeding in an anti-clockwise direction to self-transcendence. According to Schwartz (2012), motivational values form a continuum of related motivations. This causes the model to take a circular form. The closer the proximity of any two values in either direction around the circle, the more similar their underlying motivations. In contrast, the more distant any two values are along the circle the more antagonistic their motivations. Actions in pursuit of any value have consequences that conflict with some values but are congruent with others. However, this is largely dependent on the context in which actions take place. Figure 8 (above) shows conflict and congruity among values, which can be contrasted diagonally as conservation vs. openness to change and self-enhancement vs. self-transcendence. Each of these is now considered.

Openness to change is a higher order motivational value comprising self-direction, stimulation and hedonism. For Bandura (1977), self-direction relates primarily to the prevalence of independent thought. Individuals who are self-directed tend to be independent minded and action-choosing and tend to favour creating and exploring. Deci (1976) suggests that these motivations may be linked to the organismic needs for control, and mastery and interactional needs of autonomy and independence. Similarly, stimulation refers to motivation driven by excitement, novelty and challenge in life (Bandura, 1977, Deci, 176). Stimulation may be derived from the organismic need for variety and stimulation, and to maintain an optimal, positive (rather than threatening) level of activation (Deci, 1976). In this way, Schwartz (2012) notes that stimulation and self-direction are closely linked. For Sagiv and Schwartz (2000), hedonism relates to pleasure or sensuous gratification for oneself, associated with the organismic need for pleasure and satisfaction. According to the motivational values model, hedonism falls between openness to change and self-enhancement, since both of these higher order values may often comprise hedonistic motivations.

Self-enhancement is a higher order motivational value that comprises hedonism, achievement and power. McLelland (1961) suggests that achievement relates to personal success, through the demonstration of competence according to social standards. Schwartz (1992) argues that this value is necessary for individuals to survive and for groups and organisations to reach their objectives. Power is defined as social status and prestige, control and/or dominance over people

and resources (Lonner, 1980) Interpersonal relationships often have power/dominance dynamics and societies therefore often tend to treat power as a value (Schwartz, 1992, 2012). Power is focused on social esteem; it is the attainment or preservation of a dominant position within the more general social system (Lonner, 1980).

Conservation is a higher order motivational value made up of security, conformity and tradition. Maslow (1965) defines security as one of the most fundamental human needs, related to safety, harmony and stability of society, of relationships and of self. For Schwartz (2012), security is derived from basic individual and group requirements; some are individual interests while others are wider group interests. Conformity relates to a restraint of actions, inclinations and impulses likely to upset or harm others and violate social expectations or norms (Parsons & Shils, 1951). Conformity stems from the requirement that individuals inhibit inclinations that might disrupt or undermine smooth interaction and group functioning. Conformity and tradition are terms often used interchangeability. In this context however, tradition refers to respect, commitment, and acceptance of the customs and ideas that one's culture or religion provides (Durkheim, 1954). Tradition is often associated with practices, symbols, ideas and beliefs that represent their shared experience and fate, which then become sanctioned as valued group customs and traditions and symbolises the groups' solidarity, expresses its unique worth and contributes to its survival (Schwartz, 2012). Indeed, tradition and conformity are similar; Parsons and Shils (1951) suggest that tradition and conformity values are very close in their motivation, they share the common goal of subordinating someone to socially imposed expectations.

Self-transcendence is a higher order motivational values comprising universalism and benevolence. For Maslow (1965), benevolence relates to preserving and enhancing the welfare of those with whom one is in frequent personal contact. Thus, benevolence is derived from the requirement for smooth group functioning and for organismic need for affiliation (Deci, 1976). Universalism relates to understanding, appreciation, tolerance and protection for the welfare of all people and nature (Rokeach, 1973) Universalism is derived from survival needs of individuals and groups (Deci, 1976; Schwartz, 2012).

In the context of this research, however Schwartz's model of motivational values is considered comprehensive because it accounts for both extrinsic and intrinsic motivational factors. Cross-cultural research has indicated significant individual differences in the importance attributed

to each of the ten values that comprise the model (Schwartz, 1992, 2012). Despite these differences, the hierarchical order of values across cultures seems to remain relatively similar. It may be possible that this this 'pan-cultural hierarchy' may derive from common human nature (Rokeach, 1973).

Schwartz (2012) asserts that the basic social function of values is to motivate and control the behaviour of group members through two interlinking mechanisms: i) that values serve as internalised guides for individuals, and ii) that individuals invoke values to define, justify or elicit particular behaviour as socially appropriate. Values can therefore be considered as critical motivators of behaviours and attitudes. Consequently, individuals who ascribe to differing value systems may view the adoption of new modes of productivity with entirely different interpretations. In other words, motivational values may be significantly associated with technological propensity and furthermore, may mediate the relationship between technological propensity and productivity. Here, hypotheses A3 and A6 are introduced:

> *HA3: Motivational values are significantly associated with technological propensity*
> *HA6: Motivational values mediate the relationship between technological propensity and productivity*

Motivational values theory incorporates biological, social and psychological motivational goals of individuals, and relates these values to individual behavior (Schwartz, 1992). In the context of this research, motivational values theory therefore offers a useful perspective on individual differences, beyond the relatively limited scope of personality.

Previous research on the motivations of scientists and R&D professionals have found that intrinsic rather than extrinsic motivations tend to lead to innovative performance and productivity (Farris & Cordero, 2002; Gezelter, 2015). As previously discussed, it has been argued that academic researchers have an obligation to produce research outputs that address the needs of social stakeholders (Radder, 2010; Fenton, Chillag & Michael, 2015). These obligations however, may be more closely aligned to extrinsic drivers of motivational, rather than those that are intrinsic. Grant (2008, p. 48) argues that some forms of work productivity may be positively related to 'prosocial' motivations, or "the desire to benefit other people." In other words, the desire to perform one's job well, may be related to universal or benevolent motivations. In this case, academic research may be associated with more intrinsic motivational

drivers. Interestingly, open source contributors have been found primarily to be driven to contribute by intrinsic motivation, particularly in terms of enjoyment, creativity, user need, intellectual stimulation and learning (Lakhani & Wolf, 2003). Information providers are willing to perform these tasks without remuneration (Lakhani & von Hippel, 2003). Similarly, crowdfunding initiatives have been found to have altruistic motivations (West & Lakhani, 2008). Crowd-work motivation however, may be dependent on contextual factors. For example, Kittur (2010) finds that MTurk crowd-workers tend to be motivated by self-serving objectives, since MTurk crowd-workers are paid for their contributions. Work climate perceptions are discussed next.

2.5.4 Work Climate Perceptions

Scott and Bruce (1994) suggest that organisational climate may be one of the most important determinants of workplace innovation. Following James, Hater, Gent and Bruni (1978: 783), climate is defined as individual cognitive representations of the organisational setting "expressed in terms that reflect psychologically meaningful interpretations of the situation". This model posits that leadership, work group relations, and problem-solving style affect individual behaviour directly and indirectly, through perceptions of a 'climate for innovation'. Similarly, organisational climate can be broadly defined as an intervening variable between the context of an organisation and the behaviour of its members; or an indication of how employees experience their organisations (Patterson et al., 2005). In a study which involved R&D professionals, Scott and Bruce (1992) find that task routine may negatively moderate the relationship between climate and performance. This is of particular interest in the context of this research, given that some of the work processes of academic research may in some cases have become routinised (Anderson, et al., 2004).

Building on their findings, Scott and Bruce (1992) introduce a model of innovative behaviour in the organisational context, defining innovative behaviour as the outcome of organisational climate, leadership, work-groups and problem-solving style. Leadership and work-groups are beyond the scope of this research. Organisational climate and problem-solving style are briefly considered.

Studies at the organisational, group and individual level have offered empirical support for the effects of climate on innovative behaviour (Scott & Bruce, 1994; Parker, Baltes, Young, Huff,

Altmann, Lascot & Roberts, 2003; Radaelli, Lettieri, Mura & Spiller, 2014). At the individual level, climate is a cognitive representation of an organisation (Scott & Bruce, 1994). Individuals respond primarily to cognitive representations of environments, rather than the actual environment itself (Gavetti & Levinthal, 2000). Thus, climate represents a set of signals received by individuals concerning organizational expectations for behaviour and the potential outcomes of such behaviour. Individuals then use this information to formulate expectations and instruments. Moreover, individuals also respond by regulating their own behaviour, to realise positive self-evaluative consequences, such as self-satisfaction and self-pride (Bandura, 1988; 1991).

Some characteristics of innovative climates that have been discovered include: i) performance-reward dependency and organisational flexibility; ii) orientation to creativity and innovative change; iii) support for independence in the pursuit of new ideas; and iv) tolerance for diversity (Kanter, 1983; Lee, Kim & Kim, 2006). An adequate supply of resources such as equipment, facilities and time have also been found to be critical to innovation (Amabile, 1988; Kline & Rosenberg, 2010). A combination of these factors may therefore produce an innovative organisational environment or climate. Scott and Bruce (1994) find that the degree to which individuals perceive organisational climate as supportive of innovation is very strongly and positively associated with their innovative behavior (or innovative work performance).

Problem-solving styles range from the more conventional associative styles to those that are intuitive (Scott & Bruce, 1992). Associative problem solving is based on habit, routines, rules, rationality and logic and is commonly associated with ‘conventional solutions’ to problems, while intuitive (or bisociative) problem solving involves overlapping domains of thought, lack of attention to rules and boundaries, emphasis on imagery and intuition, and is more likely to generate novel solutions, or innovation (Adams, 2003). For Scott and Bruce (1992), neither style is preferable in terms of outcome. Instead, what is key is the combination of problem-solving style, in conjunction with task type and work environment that determines individual task performance and the ability of the individual to be flexible at any stage of the innovation process. For organisations in which innovation is critical (such as is the case in the context of academic research), managers should strive to adopt the intuitive problem-solving style. Conversely in organisations that rely on routinised, systematic functionality (for example, manufacturing plants), managers should seek to adopt the associative problem-solving style.

Difference in organisational problem-solving styles also impacts climate perceptions amongst employees (Adams, 2003). When a task is routine or when individual discretion is low, the relationship between climate and innovative behaviour is likely to be weaker than when the task is non-routine and high discretion is granted. Given the purported routinised state of some forms of academic research (Anderson, et al., 2004), it is possible then that the climates in which academic research is conducted may not be conducive to innovation. As previously discussed, openness to experience, as a personality trait tends to decrease with age (Specht, et al, 2011). Costa and McCrae (1990) note that individuals with lower levels of openness to experience tend to follow conventional ways of thinking and in some cases, may also be more risk averse than others. Similarly, Scott and Bruce (1994) suggest that career stage is negatively associated with innovative output; the further an individual has progressed along their career, the less likely they are to be innovative. In the context of this research therefore, it may be likely that more experienced (older) academic researchers would likely have lower technological propensities than their less experienced counterparts, favouring instead conventional methods that have proven successful in the past.

A wide spectrum of conflicting views exists on climate. Patterson, et al. (2005) provide a historical overview of organisational studies, ranging from the individual to aggregate levels of analysis. McLean (2005) differentiates between the terms ‘climate’ and ‘culture’, which are often used interchangeably (both are used to describe employees’ experience of their organisation), but which are not the same. For Schneider (2000), climate is behaviourally orientated and represents the descriptions of the things that happen to employees in organisations. In contrast, culture comes to light when employees are asked why these patterns exist; and it is defined by shared values, common assumptions and patterns or beliefs which are held by organisational members. Thus, climate can be understood as a surface manifestation of culture (Schneider, 2000; McLean, 2005).

Patterson, et al. (2005) introduce the Organisational Climate Model (OCM), a multidimensional, global and aggregate approach to organisational climate, at the individual level of analysis. The OCM (see Figure 9, below) offers a relatively comprehensive and flexible approach to the assessment of organisational climate and is both theoretically grounded and empirically validated (Patterson, et al., 2005).

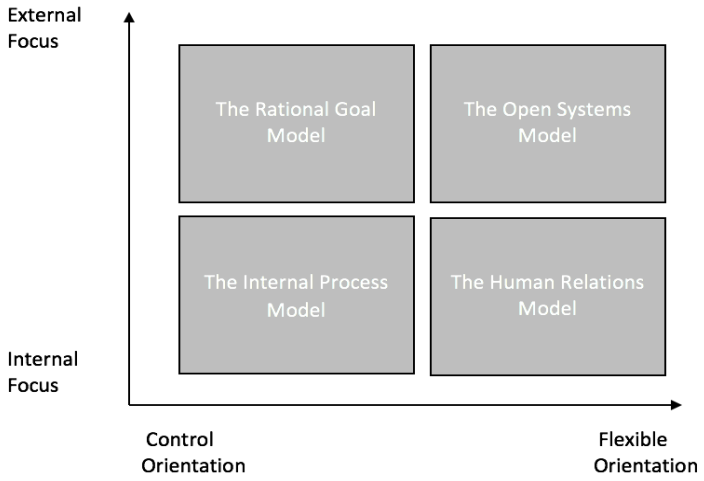


Figure 9: The Organisational Climate Model (adapted from Patterson, et al., 2005, p. 386)

Schneider (2000) refutes the use of general multidimensional measures and argues for a facet-specific climate approach, where climate has a focus and is tied to something of interest. In this case, the dimensions of organisational climate would differ depending on the purpose of the investigation. Patterson et al. (2005) echo these assertions and suggest that dimensions of the OCM, while comprehensive, are customisable, depending on the purpose of the investigation. Based on these assertions, it is argued that in the context of this research, the contrast between the Internal Process Model (IPM) and the Open Systems Model (OSM) would seem to be the most pertinent focus of interest.

According to the OCM, The Open Systems Model (OSM) relates to climates that have an external focus and a flexible orientation, where readiness, change and innovation are emphasised, and values are associated with growth, resource acquisition, creativity and adaptation (Patterson et al., 2005). The climate dimensions of the OSM, which are grounded in seminal climate literature, include the following:

- **Flexibility and innovation:** an orientation towards change (King & Anderson, 1995) and the extent of encouragement and support for new ideas and innovative approaches (West & Farr, 1990).
- **Outwards Focus:** the extent to which the organisation is responsive to the needs of the customer and the marketplace in general (West & Farr, 1990).

- **Reflexivity:** a concern with reviewing and reflecting upon objectives, strategies, and work processes, in order to adapt to wider environments (West, 2002).

In contrast, the Internal Process Model (IPM) reflects internal focus and a control orientation that emphasises stability, where the effects of environmental uncertainty are ignored or minimised. Coordination and control are achieved by adherence to formal rules and procedures and represent the classic bureaucracy (Patterson et al., 2005). The climate dimensions of IPM, which are grounded in seminal climate literature, include the following:

- **Formalisation:** a concern with formal rules and procedures (Hall, 1991)
- **Tradition:** the extent to which established ways of doing things are valued (Anderson & West, 1998)

Patterson et al. (2005, p. 397) comment on the contrast between the OSM and IPM: "in older companies [which tend to adopt the IPM], systems and patterns of behaviour tend to become institutionalised, acting as a source of organisational inertia. This inertia sets limitations on the ability of organisations to adapt." Both formalisation and tradition have been found to be negatively associated with "adoption of a number of management practices associated with the 'new manufacturing paradigm'". Conversely, those organisations that strive to adopt OSM-type climates tend to be more likely to adopt new management processes and in broad terms, tend to be more innovative. Similarly, the dimensions of OSM climates, including flexibility, innovation, outward focus and reflexivity have been found to be positively associated with innovative behaviour, performance and output.

Although the university context differs from the organisational context, certain similarities may exist. Lee and Bozeman (2005) find that university climates that encourage inter-disciplinary collaboration are more likely to be highly research productive, and as a result, produce more innovative research output. Behrens and Gray (2000) suggest that cooperative research between universities and industries may in some cases stifle academic freedom. Thus, universities that actively pursue cooperative research with private industry may experience a decline in academic freedom. As a result, university climate and climate perceptions may tend towards IPM-type models (Patterson, et al., 2005). Conversely, those universities that do not pursue cooperative research might suffer from a relative lack of research funding (Behrens &

Gray, 2005), although perception of academic freedom may increase. Here, Hypotheses A4 and A7 are introduced:

> *HA4: Climate perceptions are significantly associated with technological propensity*
> *HA7: Climate perceptions mediate the relationship between technological propensity and productivity*

Given the literature discussed above, universities that are able to find a balance between academic freedom and financial stimulus and that are able to encourage inter-disciplinary collaboration may be more likely to be classified as OSM, where flexibility, innovation, outward focus and reflexivity are favoured. Conversely, those universities that tend to rely too heavily on industrial cooperation or that do not encourage inter-disciplinary collaboration might be classified as IPM, where tradition and formalisation are favoured. Academic researchers in OSM universities may therefore have higher levels of technological propensity, since open climates might be more conducive to the adoption of unconventional modes of productivity. Academic researchers in IPM universities may seek to avoid new and unconventional modes of productivity and may therefore have lower levels of technological propensity. Human capital investments are discussed next.

2.5.5 Human Capital Investments (HCI)

For Krugman (1997, p. 11), "productivity isn't everything, but in the long run, it is almost everything…. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise output per worker". Higher productivity levels allow society to reinvest in human capital, which in turn results in even higher productivity (Garton, 2017). The most common investment in human capital occurs in the form of increased salaries and wages, but these alone are not sufficient human capital investments to promote productivity (Garter & Mankins, 2017).

Human Capital Investments (HCI) refers to the investment of resources that contribute to the development (or appreciation) of an individual, or alternatively, the depreciation of an individual (Bosma et al., 2004). While traditional, neoclassical models of investment focused

primarily on physical capital, the work of Becker (1962, 1994) attributes importance to the individual-level accumulation of 'productive knowledge'.

Becker (1962, p. 9) developed what is now commonly referred to as "the economic approach to human behaviour", by exploring the various facets of human behaviour through a set of simplified assumptions, which include a forward-looking stance, consistent rationality, and stable and persistent preferences. Such choices are all constrained by income, time, imperfect memory and calculating abilities and the opportunities available at a given time. For Becker (1962, p. 15)

> Schooling, a computer training course, expenditure on medical care and lectures on the virtue of punctuality and honesty are capital … in the sense that they improve health, raise earnings, or add to a person's appreciation of a literature over much of his or her lifetime. Consequently, it is fully in keeping with the capital concept as traditionally defined to say that expenditures on education, training, medical care, etc., are investments in capital. However, these produce human, not physical or financial capital because you cannot separate a person from his or her knowledge, skills, health or values the way it is possible to move financial and physical assets while others stay put.

HCI theory describes the expenditures on training, education, and medical care and lifestyle choices as a form of individual level self-invested capital, that is directly associated with productivity (de la Fuente, 2011). The term 'human capital' is used in describing intangible assets such as knowledge, expertise, skills and values that cannot be separated from the individual (Blundel et al., 1999). Becker (1994, p. 11) offers a succinct definition of human capital as "activities that influence future real income through the embedding of resources in people". Assets such as education and training are considered vital elements of human capital. Research has shown direct associations with level of education and training and personal income, or 'return on investment' (Blundel et al., 1999). Becker (1962) argues that investment in human capital has an important effect on earnings (or productivity).

The chief principle of HCI theory relates to factors other than physical resources (namely, intangible assets), which contribute to income growth. Becker (1962) lists i) education, schooling and on-the-job training; ii) family; iii) the economic, political or social system (such as an individual's knowledge of salaries in a related job); iv) and productive wage increases

(improvement in emotional and physical health), all as different types of investment in human capital. Each of these is briefly discussed. According to Becker, (1994, p. 17) "education and training are the most important investments in human capital". High school and college education has been shown to significantly raise an individual's income, with the earnings of more educated people almost always being well above average (Garton & Mankins, 2017). Becker (1994) notes that high school and college are not the only components of education, training and schooling, but that 'on-the job training' can be as, if not more, important and a better predictor of future earnings. Mincer (1988). suggests that the total investment in on-the-job training may be almost as large as the investment in education, but monetary earnings (salary or wages) are not the only positive outcome of investment in education. Recent studies have also shown that investment in education promotes health, reduces smoking, raises the propensity to vote, and improves birth control knowledge (Vila, 2000).

Family structures, or 'familial situations' are another form of human capital and have been shown to significantly influence the individual's knowledge, skills, values and habits (Becker, 1994). This is especially true in the case of relationships between parents and children, even in predevelopment stages before formal schooling. Parental influence has been shown to impact marital stability, education and motivation later in life (Vila, 2000). Although earnings of parents can be seen as a positive effect on children's motivation, the relationship is variable and not always strong (Becker, 1994) in all cultural contexts (Garton & Mankins, 2017).

The expansion of scientific and technical knowledge (rather than the traditional notion of additional capital and land) raises the productivity of labour and other inputs in production (Becker, 1994). Thus the value of education, technical schooling, and on-the-job training increases with the systematic application of scientific knowledge of production. This is because the growth of tacit knowledge is embodied within people (von Hippel, 1976) who contribute to output. Becker (1994) cites the example of persistent national-level economic growth in countries such as the USA, Japan and South Korea due to increasing investments education, schooling and training and healthcare. Moreover, education and training is also considered helpful in coping with rapidly advancing and changing technologies (Becker, 1994, Garton & Mankins, 2017). Knowledge of new technologies has also been shown to enhance productivity, in both the manufacturing and service sectors (Becker, 1994; Black & Lynch, 1996). Hypothesis B1 is introduced here:

HB1: HCI are significantly associated with productivity

The measurement of human capital investment is generally considered problematic (Blundel, et al., 1999), since "investment in human capital usually extends over a long and variable period, so the amount invested cannot be determined from a known investment period" (Becker, 1962, p.30), Nevertheless, the relationship between human capital investments and work productivity has been investigated (Black & Lynch, 1996; Garton & Mankins, 2017). Bishop (1994) concludes that employer-provided training can raise productivity by almost 16%. Black and Lynch (1996) find that human capital is an important determinant of establishment productivity since the average educational level of the establishment has a positive and significant effect in both the manufacturing and non-manufacturing sectors. Furthermore, Black and Lynch (1996) find that a 10% increase in average education in the establishment (approximately one year of schooling) will lead to a 4.9 to 8.5% increase in productivity in manufacturing and a 5.9 to 12.7% increase in productivity in non-manufacturing. Since these ranges are somewhat large, the impact of education on establishment productivity is substantial. Firms' recruitment and selection strategies are also found to be associated with productivity. Those firms that emphasise school and college grades as important priorities in hiring, tend to show higher levels of productivity than those which do not. In terms of on-the-job training, Black and Lynch (1996) find that the greater the proportion of time spent in formal off-the-job training (for manufacturing), the higher the productivity. This perhaps can be attributed to training which occurs outside of working hours and which therefore lowers the output loss associated with on-the-job training. For non-manufacturing, Black and Lynch (1996, p. 266) find that both types of training (on-the-job and off-the-job) enhances productivity. Specifically, they find that training of technological skills significantly enhances productivity: "It is not so much *whether* you train the workers, but rather, *what you train the workers in*, that affects the establishment productivity."

Black and Lynch (2001: 434) investigate the impact of workplace practices and information technology and human capital investments on business productivity and corroborate their earlier findings; that "it is not whether an employer adopts a particular work practice, but rather how that work practice is actually implemented within the establishment that is associated with higher productivity". Productivity is higher in businesses with more educated workers and workers with greater technological know-how. Productivity is also higher in firms with workers who are trained in using new technologies. Black and Lynch (2001) investigate the

relationship between computer use and productivity, finding that the knowledge and adoption of computers for work purposes may increase establishment productivity significantly. These findings are useful in the context of this research, since technological know-how and computer use are underpinned by similar mechanisms underlying technological propensity. Thus, Hypothesis A8 is introduced here:

HA8: HCI mediates the relationship between technological propensity and productivity

Seibert, Crant and Kraimer (1999) argue that personality variables should be included in models of career success, work performance and productivity. Similarly, Heckman (2000) by argues that the extent of human capital investments in related to motivations. Following Amabile (1997) and Lam (2011), the motivation to be creative (and therefore, innovative) may be related to work climate perceptions. Based on these threads of literature, Hypotheses B2, B3 and B4 are introduced:

HB2: Personality mediates the relationship between HCI and productivity
HB3: Motivational values mediate the relationship between HCI and productivity
HB4: Work climate perceptions mediate the relationship between HCI and productivity

This concludes the derivation of Hypotheses A and B. However, the interrelationships around technological propensity, HCI and productivity may also be moderated by certain individual-level differences other than personality, motivational values and work climate perceptions. Bourdieu (1992) uses the term habitus to describe a set of acquired schemes of dispositions, perceptions and appreciations, which orient practices and give them meaning, as a result of actions and interactions with others. According to Thorpe (2009, p. 499), habitus is "both the embodiment of our social location (i.e. class, ethnicity, race, sexuality, gender, generation and nationality) … and the structure of social relations that generate and give significance to likes and dislikes with regard to practice and action." Following both Bourdieu (1992) and Thorpe (2009), variables such as gender or nationality (or in the case of academic researchers 'field of study') may therefore represent the embodiment of experiences and socialisations that individuals are exposed to. The moderating effects of gender and field of study on the relationships around technological propensity, HCI and productivity are now introduced and discussed. Gender is considered fist, as follow.

2.5.6 Gender

It is argued that it is necessary in the context of this research to discuss gender from the perspective of Ascription Theory. For Marwell (1975, p. 445) "in every culture women and men are assigned disparate functions and patterns of behaviour well beyond those dictated by clear psychological differences". The classical sociological view on social stratification and ascription imputes gender inequality to Conflict Theory (Reskin, 1988), where dominant groups (here referring to the male gender) exercise control over resources to maintain privilege and thereby, exemplify motive-based explanations. As a result, gender inequality occurs due to individuals pursuing their own interests (Reskin, 1988) which may in turn lead to gender discrimination. Gender may be seen to act as a proxy for the interaction between cultural standards and societal norms, which may significantly impact productivity. This is particularly relevant in the case of academia and academic research productivity (Leahey, 2006).

Gender diversity in R&D teams, however, has been shown to be positively related to the production of radical innovations (Marvel & Lee, 2011). Nevertheless, research has shown perceived gender roles within the context of an organisation to have an impact on innovative behaviour; since men are often perceived to be more innovative than women (Boyd, 2013). Therefore, "gender roles … may inhibit (in the case of women) or facilitate (in the case of men) the likelihood of innovative behaviour" (Millward & Freeman, 2002, p. 96). Perceptions on gender roles also extend to acceptable levels of risk; women are often expected to be more risk-averse than men (Millward & Freeman, 2002). Research has indicated that a gender gap in science, technology, engineering and mathematics (STEM) professions as well as in the adoption and use of new technologies does exist (Samson, 2006). Buré (2007) refers to the 'glass ceiling' as well as issues relating to the instability of the professional pipeline, as precursors to the innovation gender gap. Despite this, research on the status of gender equality in innovation and technology has identified enhanced employee recruitment and retention from a wider pool of skilled workers (Pugliesi, 1995), improved corporate image and reputation (Jackall, 1988), and greater innovation and enhanced marketing opportunities (Chaves, 1996) as potential business advantages for employing gender-equality policies. Danilda & Granat Thorslund (2011, p. 28) encourages "gender analysis" in order to "reveal unexploited innovative opportunities." Interestingly, research on the association between gender and innovation has revealed that male and female innovation tends to differ in nature; women tend to angle towards innovations that are largely inspired by local needs to achieve social ends,

while this is not the case for men (Blake & Hanson, 2005). Given these differences in levels and types of innovativeness between genders, it may be possible that gender moderates the relationship between technological propensity and productivity. Following the findings of the research discussed above, male individuals may experience a stronger positive relationship between technological propensity and productivity than female individuals. Here, Hypothesis C1 is introduced:

> *HC1: Gender significantly moderates the relationship between technological propensity and productivity*

Leahy (2006) notes as a general trend, women are slightly less research productive than men in the academic context, as a result of the spill-over effect stemming from 'family life', commonly associated with duties relating to maternity leave and raising children. Additionally, female academic researchers tend to specialise less than males in academic research, which may be another contributing factor to lower levels of research output in females (Wenneras & Wold, 2001; Leahy, 2006). Hypothesis C3 is introduced here:

> *HC3: Gender significantly moderates the relationship between HCI and productivity*

In consideration of self-determination theory, it has been suggested that the difference between men and women in levels of motivation are essentially "near-zero, thus representing negligible differences between men and women" (Guérin, Bales, Sweet & Fortier, 2012).In consideration of personality, based on the 'Big Five' model (Costa & McCrae, 1990), women were found to be more susceptible to score highly on traits such as Agreeableness and Neuroticism, while men were found to score more highly on traits such as Extroversion and Openness and differences in Conscientiousness were generally evenly spread (Chapman, Duberstein, Sörensen & Lyness, 2007). Differences in field of study (or 'area of expertise') are discussed next.

2.5.7. Field of study

This study follows the seminal research of Gonzalez-Brambila and Veloso (2007) on differences in research productivity among the different 'scientific areas'. A global study

conducted by Gonzales-Brambila and Veloso (2007) investigated the differences in academic research productivity by 'area of knowledge' by assessing total number of ISI-indexed journal publications over time. While a number of previous studies documented significant heterogeneity in the pattern of publications across areas (Cole, 1979; Xie & Shauman, 1998), few have made systematic efforts to investigate differences in productivity as per 'scientific area', or 'field of study'. In their study, Gonzales-Brambila and Veloso (2007) demarcated respondents by area, including i) social and humanities, ii) biology and chemistry, iii) exact sciences, iv) agricultural sciences and biotechnology, v) engineering and vi) health sciences and discover a wide variation among different areas. The results of the study show that academic researchers associated with the area termed 'health sciences' tend to have higher levels of research productivity than their counterparts. These are followed by 'exact sciences' (physics, mathematics and related fields), biology and chemistry, engineering, agricultural sciences and biotechnology and finally social and humanities, respectively. According to Gonalez-Brambila and Veloso (2007), researchers in health sciences, exact sciences, biology and chemistry generally start publishing at a younger age and therefore have longer productive careers. In contrast, those academic researchers on the lower end of the research productivity spectrum, specifically those in the area termed 'social and humanities' are have shorter productive careers because they generally start to publish at a later age than their contemporaries. Gonzales-Brambila and Veloso (2007: 1037) also suggest that knowledge in the more research productive areas may be "more easily codified, making its transmission through published papers easier," while researchers in low productive areas may often work primarily "in research topics that are mostly of local interest (regional or country level), and their results tend to be diffused in local journals that are not part of the ISI databases". Hypotheses C2 and C4 are introduced here:

> *HC2: Field of Study significantly moderates the relationship between technological propensity and productivity*
>
> *HC4: Field of Study significantly moderates the relationship between HCI and productivity*

For the purpose of this research, areas of knowledge (or, fields of study) are divided into four distinct fields, including i) Commerce, Law and Management, ii) Sciences, iii) Humanities and iv) Health, which is in line with the general trend of faculty division in South African

universities. A basic diagrammatic representation of the literature is provided in Figure 10, below Thereafter, this chapter is concluded.

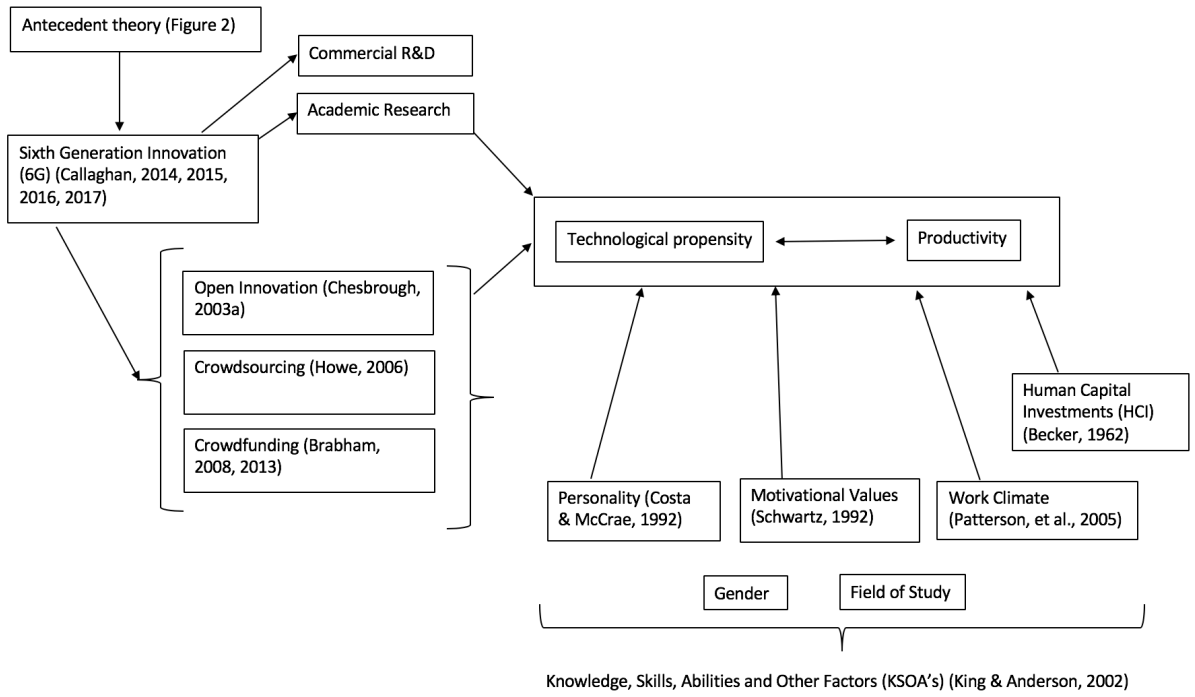


Figure 10: Diagrammatic representation of the literature review

2.6 CHAPTER CONCLUSION

In this chapter, the progression of scientific innovation and knowledge was discussed. Following Gray (2009), Rothwell (1994) and Schwab (2016), the progress of science, technology and innovation was likened to the process of biological evolution, leading to an eventual theorised' perfect state'. Seminal innovation management and knowledge management literature was reviewed. Rothwell's (1994) 5G model of innovation was discussed, as was Callaghan's (2014a) proposed 6G model of innovation and probabilistic innovation. Probabilistic innovation, and the underlying probabilistic mechanism was suggested as a potential solution to the problem of innovation failure, and academic research routinisation. Certain proposed 6G models, which incorporate the use of both crowdsourcing and crowdfunding were reviewed and their potential and applicability in the academic research context considered. Technological propensity, or the extent to which individuals seize

opportunities related to certain new modes of productivity associated with scale advantages (such as crowdsourcing and crowdfunding) was defined. Productivity, the dependent variable under study in this research was discussed and the primary research question, related to the relationship between technological propensity and productivity was derived.

Next, the determinants of academic research productivity were discussed. These included personality, motivational values, work climate perceptions, Human Capital Investments (HCI), gender and field of study. Each of these were discussed, in relation to technological propensity and productivity and further hypotheses were derived. Having discussed the literature pertinent to the theoretical model introduced in Chapter 1 and upon which this research is conducted, the research methodology is now introduced and discussed.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 INTRODUCTION

The previous chapter provided a review of the literature. The theory of 6G innovation, which relates to certain new technological and methodological advancements that may offer significant economies of scale, was introduced and discussed. Hypotheses were derived from the literature review section. This chapter extends the content of the previous chapter by providing an overview and justification for the methodological precedents that guide this research. This chapter proceeds as follows. First, an overview of the research methodology is provided. This overview pertains to the appropriateness of the research design and the location of the research in a paradigmatic sense. Second, qualitative and quantitative methods of research are discussed. Third, the populations, samples, sampling techniques, research instruments, data collection processes, reliability and validity are reviewed. Fourth, the processes of qualitative and quantitative analyses are described. Finally, limitations and ethical considerations are examined. A brief overview of the study's methodology is now provided.

3.2 BRIEF OVERVIEW

A mixed methods approach was undertaken. For Creswell, Klassen, Clark and Smith (2011), mixed methods research offers a better, integrated understanding of the research problems than might a monomethod approach. It is for this primary reason that a mixed methods approach was undertaken in this research. A qualitative study was conducted to justify the inclusion of certain individual-level variables for quantitative testing. A modified inductive qualitative methodology was applied (Thomas, 2006). A quantitative study was undertaken to test theory (Gabriel, 2013). The combination of qualitative and quantitative methods is referred to as mixed methodology. For Creswell (2003, p. 4):

> Mixed methods research has come of age. To include only quantitative and qualitative methods falls short of the major approaches being used today in the social and human sciences… a mixed methods approach is one in which the researcher tends to base knowledge claims on pragmatic grounds (e.g. consequence-oriented, problem-centered, and pluralistic). It employs strategies of inquiry that involve collecting data either simultaneously or sequentially to best understand research problems. The data collection also involves gathering both numeric information (e.g. on instruments) as well as text information (e.g. on interviews) so that the final database represents both quantitative and qualitative information.

This study seeks to evaluate interest in certain new technologies and methodologies that may enable economies of scale, and their relation to research productivity, at the individual level of analysis. A model designed to delineate the relationship between two constructs; an individual's technological propensity and productivity, was used as a baseline to investigate this relationship. According to Creswell (2003; p. 22), "a mixed methods design is useful to capture the best of both quantitative and qualitative approaches." Moreover, the use of mixed methods has several advantages over other methodologies. Johnson and Onwuegbuzie, (2004, p. 19), offer a broad overview and comparison of the strengths and weaknesses of qualitative, quantitative and mixed methods:

> [M]ixed methods research… is an attempt to legitimate the use of multiple approaches in answering research questions, rather than restricting or constraining researchers' choices (i.e. it rejects dogmatism) …Many research questions and combinations of questions are best and most fully answered through mixed research solutions.

Johnson and Turner (2003, p. 301) refer to the fundamental principle of mixed research. According to this principle, "researchers should collect multiple data using different strategies, approaches, and methods in such a way that the resulting mixture or combination is likely to result in complementary strengths and non-overlapping weaknesses." For Johnson and Onwuegbuzie (2004), this principle justifies the use of mixed methods research, suggesting that the combination of qualitative and quantitative methods may be superior to single-method studies. It was deemed appropriate therefore, to employ a mixed methods approach.

This research employs both inductive and deductive approaches. During the qualitative study (Study 1), an inductive approach, which entails a focus on theory development, is employed. During the quantitative studies (Studies 2 and 3), a deductive approach, which entails a focus on theory testing, is employed (Gabriel, 2013). The purpose of the inductive qualitative study is to assess the human resources management (HRM) determinants of breakthrough research productivity. The purpose of the deductive quantitative studies is to assess the relationship between technological propensity (or the extent to which individuals seize opportunities related to new technologies that offer significant economies of scale) and productivity.

Prior to data collection, a theoretical model, based on global research was derived from literature. Thereafter, the processes of data collection occurred in two concurrent phases.

Qualitative data were collected through a process of interviews with notable innovators. Two quantitative instruments were used to collect data from two different quantitative samples. The first quantitative sample comprised of South African academic researchers. The second quantitative sample comprised of users of Amazon's Mechanical Turk (MTurk). The findings of the qualitative study provided the basis for an inductive assessment of the determinants of breakthrough research productivity. A model of propositions was derived from qualitative data and subsequently compared to a theoretical model derived from the literature. As mentioned, the theoretical model is based on global research and therefore may not capture context-specific nuances. However, the grounded model of propositions derived from qualitative analysis may provide a means to capture these nuances more effectively.

The findings of the empirical studies were compared to the theoretical model derived from the literature. The objective of this this process is to provide a holistic analysis of the relationship between technological propensity and productivity, spanning three different levels of productivity. The outcome of this process is a derivation of recommendations for managers of academic research and R&D related to the adoption of certain new modes of productivity, which may enhance the rate at which breakthrough (or radical) innovations are produced. The key research question underpinning this research is:

What is the relationship between technological propensity and productivity?

To answer the research question and sub-questions, five basic hypotheses are derived from the literature. These hypotheses were tested to establish significant associations between the variables under study. A discussion of the paradigmatic location of the research or, the "set of beliefs, values and assumptions… regarding the nature and conduct of research" (Johnson & Onwuegbuzie, 2004, p. 24) now follows.

3.3 PARADIGMATIC LOCATION OF THE RESEARCH

Certain assumptions underpin this research. These assumptions relate to epistemology (or the foundation of knowledge) and ontology (or the assumptions about the nature of the phenomena to be explored) (Burrell & Morgan, 1979; Cohen, Manion & Morrison, 2002; Marshall & Rossman, 2014). According to Johnson and Onwuegbuzie's (2004) classification, this research, comprising of a mixed methodology, is located in the pragmatic paradigm.

Pragmatism is a deconstructive paradigm that advocates the use of mixed methods in research, "sidesteps the contentious issues of truth and reality" (Feilzer, 2010, p. 8) and "focuses instead on 'what works' as the truth regarding the research questions under investigation (Tashakkori & Teddlie, 2003b, p. 713). In this sense, pragmatism rejects a position between the two opposing viewpoints. Essentially, pragmatism rejects the choice associated with the 'paradigm wars' (Johnson & Onwuegbuzie, 2004; Onwuegbuzie, Johnson & Collins, 2011).

According to Felizer (2010), pragmatism sidesteps the contentious issues of truth and reality, accepts, philosophically, that there are singular and multiple realities that are open to empirical enquiry and orients itself toward solving practical problems in the "real world" (Creswell Hanson, Clark & Morales, 2007; p. 20). In this sense, pragmatism allows a researcher to be free of mental and practical constraints imposed by the "forced choice dichotomy between positivism and constructivism" (Creswell, Hanson, Clark & Morales, 2007, p. 27). Researchers do not therefore have to be "the prisoner of a particular [research] method or technique (Robson, 1993, p. 291).

Pragmatists' view of the measurable world relates more closely to an "existential reality" (Dewey, 1925, p. 40), a reference to an experiential world with different elements or layers, some which are objective, other subjective and some a mixture of the two. Dewey's (1925) seminal assertion is that the main research paradigms of positivism and subjectivism derive from the same paradigm family, in that they seek to find the 'truth', whether that be an objective truth or the relative truth of multiple realities. For Rorty (1999, p. ixx), pragmatists are "anti-dualists", that question the dichotomy of positivism and constructivism and call for a convergence of quantitative and qualitative methods. Rorty (1999) further contends that qualitative and quantitative methods are not different at an epistemological or ontological level and that they share many commonalities in their approaches to inquiry (Johnson & Onwuegbuzie, 2004; Collins, Onwuegbuzie & Johnson, 2012). Hanson (2008, p. 103) argues that the distinctions between phenomena as objective or subjective are primarily a result of political divisions among social scientists, combined with the development of distinctive skill sets for quantitative and qualitative research.

Pragmatists also hold an "antirepresentational view of knowledge" arguing that research should no longer aim to most accurately represent reality, to provide an "accurate account of how

things are in themselves" but to be useful to "aim at utility" (Rorty, 1999, p. xxvi). For Felizer (2010, p. 9), the notion of 'utility 'calls for reflexive research practice. Therefore, any inquiry begs the question of "what it is for," "who it is for" and "how do the researchers values influence the research?". Felizer (2010) also notes epistemological concerns related to pragmatism. More specifically, if phenomena have different layers, how can these be measured or observed? Mixed methods research offers to address this gap by using quantitative methods to measure some aspects of the phenomenon in question and qualitative methods for others.

Johnson and Onwuegbuzie (2004) argue that taking a non-purist, or mixed position, as is the case of this research, allows researchers to mix and match design components that offer the best chance of answering their specific research question. For example, in this research, it is hoped that the quantitative portions of this study will contribute to a greater understanding of the relationship between technological propensity and productivity across the academic research and 6G contexts. In addition, the qualitative portion of this research seeks to provide deeper insight into the nature of breakthrough research productivity and furthermore to investigate whether technological propensity does indeed influence the extent to which academic researchers are able to produce breakthrough research and thereby fulfill a purported obligation to produce societally consequential research breakthroughs (Fenton, Michael & Chillag, 2015). It is acknowledged that causality cannot be established using statistical analyses. However, this research does aim to provide a holistic perspective of the relationships in question.

This study is also associated with Creswell et al.'s (2003, p. 11) perspective of "pragmatic knowledge [which] claims … instead of methods being important, the problem is most important." This study also makes use of mixed methods to "establish a rationale for the combination of methods" (Creswell et al., 2003, p. 12). Convergent and discriminant validity (Campbell & Fiske, 1959) is ensured by the use of mixed methods, which strengthens the validity of any claims that are made.

This study also follows the assertions of Popper (1959), who makes the distinction between subjective and objective knowledge, noting that objective interpretations can be tested (unlike subjective interpretations). Thus, "every test of a theory is an attempt to falsify it, or to refute it" (Popper, 1963, p. 7). As such, qualitative research is used to develop theory and quantitative research is used to test theory (Corbin & Strauss, 2014). The level of significance chosen for

the quantitative research is 95% (Fraenkel, Wallen & Hyun, 1993). Having located the research in relation to other paradigmatic perspectives, the qualitative and quantitative research methodologies are now reviewed.

3.4 RESEARCH DESIGN

This research employed a concurrent, mixed methodology. The qualitative research follows an inductive approach. The quantitative research follows a deductive and cross-sectional research design. In this research, qualitative and quantitative data collection and analysis was conducted concurrently, or roughly at the same time (Creswell, 2003). Concurrent research designs involve a single data collection episode incorporating various qualitative and / or quantitative strategies to answer a research question (Creswell, 2003; Johnson, Onwuegbuzie & Turner, 2007). Morse (2003) offers a taxonomy of concurrent research design, which describes a parallel, rather than sequential nature of different study components, where data are collected at one point in time. In concurrent mixed-methods designs, one type of data is usually nested within another predominant data collection procedure (Creswell, 2003). Morse (2003) refers to the predominant method as the 'base study' and the nested method as the 'supplemental study'. The base study determines the overall theoretical drive of the study, while the supplemental studies provide information that cannot be gathered from the base study data. In the case of this research, Study 2 (the academic researcher analysis) is the 'base study', while Studies 1 (the qualitative analysis) and 3 (the crowd-worker analysis) are both supplemental studies. The overlap between the three studies is illustrated in Figure 11 below.

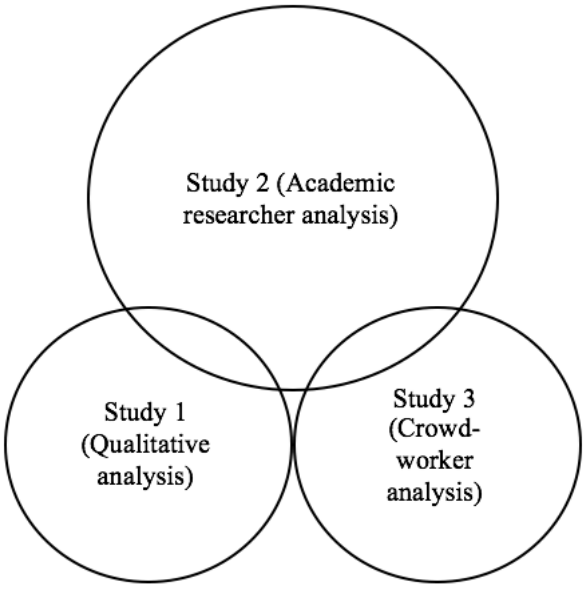


Figure 11: Components of Concurrent Mixed Methods Study (adapted from Plastow, 2016, p. 89).

The points of overlap between the three studies in Figure 10 also represents a point where integration can occur at the data collection, data analysis and interpretation stages (Morse, 2003; Tashakkori & Teddlie. 2010). One of the advantages of mixed-methods is that the strengths of one research method compensate for the weaknesses of another (Creswell, 2003). The validity of quantitative studies, and rigour and trustworthiness of qualitative studies can also be improved by verifying and elaborating findings from one component with findings from another component (Creswell, 2003; Johnson, et al., 2007). For example, using more than one measure of a particular construct, and using a variety of statistical tests may improve the validity of quantitative studies (Plastow, 2016).

Indeed, numerous other studies have followed a similar research design. For example, van Schalkwyk and Wissing (2013) evaluate academic psychosocial well-being interventions in the South African context, incorporating a mixed methods approach, where qualitative and quantitative data was collected and analysed concurrently. Collins, Onwuegbuzie and Jiao (2006) investigate the prevalence of mixed methods sampling designs in social science research and define seven different types of mixed methods designs, based two pivotal criteria. These include i) time orientation (i.e. concurrent versus sequential) and the relationship between the quantitative and qualitative sample. According to Onwuegbuzie and Collins (2007), these relationships either can be identical, parallel, nested or multilevel.

An identical relationship denotes that exactly the same sample members participate in both the quantitative and qualitative phases of the investigation. In contrast, a parallel relationship indicates that the samples for the quantitative and qualitative components of the inquiry are different but are drawn from the same underlying population. A nested relationship implies that the sample members selected for one phase of the study represent a subset of those participants chosen for the other component of the research. Finally, a multilevel relationship involves the use of two or more sets of samples that are obtained from different levels of the study (i.e. different populations). In this research, the qualitative and quantitative academic researcher samples are considered nested, since award-winning academics are considered a subset of academic researchers chosen for Study 2. However, the selection of the academic researcher sample and the crowd-worker sample represents a multilevel relationship, since both of these samples are obtained from different populations (i.e. academic researchers and crowd-workers).

Thus, this research falls between Collins, et al.'s (2006) Design 3, which involves the use of a concurrent design, using nested samples and Design 4, which involves the use of a concurrent design with multilevel sampling. An example of Design 3 is a study conducted by Hayter (1999) who implements a concurrent design, using nested samples for quantitative and qualitative facets of the study. The study's purpose was to describe the prevalence and nature of burnout in clinical nurses specialising in community-based HIV/AIDS care and to examine the association between burnout and HIV/AIDS care-related factors. In the quantitative phase, 32 community HIV/AIDS nurse specialists were administered measures designed to assess burnout and the psychological impact of working with people having HIV/AIDS. In the qualitative phase, five nurse specialists were randomly selected for a semi-structured interview. The quantitative phase involved convenience sampling, whereas the qualitative phase involved random sampling.

An example of Design 4 is a study conducted by Savaya, Monnickendam and Waysman (2000), which implemented a concurrent design using multilevel samples for the quantitative and qualitative components of the study. This study evaluated a decision support system (DSS) designed to assist youth probation officers in formulating their court recommendations. In the qualitative component, analysis of documents and interviews of senior administrators took place. In the quantitative component, youth probation officers were surveyed to determine their

use of DSS in the context of their work. These samples were selected purposively, using a maximum variation scheme (Patton, 1990). Having discussed the research design, the qualitative and quantitative research methodologies and analyses are now discussed. It is stressed that all three studies were conducted concurrently. The qualitative research methodology is discussed first, as follows.

3.5 QUALITATIVE RESEARCH METHODOLOGY

This research employs a mixed methodology, using both qualitative and quantitative methods (Creswell, 2003), for three different studies, two quantitative and one qualitative. All three studies were conducted concurrently. An inductive approach to qualitative data collection and analysis (Thomas, 2006) was employed to gather and analyse data using thematic content analysis (Miles & Huberman, 1994; Miles, Huberman & Saldana, 2014). Thomas (2006, p. 238) defines a general inductive approach to qualitative analysis, described as an approach that "primarily use[s] detailed readings of raw data to derive concepts, themes, or a model through interpretations made from the raw data by an evaluator or researcher." For Elo and Kyngas (2008; p. 107), the inductive approach is "an easily used and systematic set of procedures for analysing qualitative data that can produce reliable and valid findings." According to Thomas (2006), the general inductive approach follows three basic steps, including i) the condensing of raw textual data into a brief, summary format, ii) the establishment of clear links between the research objectives and the summary findings derived from the raw data, and iii) the development of a framework of the underlying structure of experiences or processes that are evident in the raw data. In the case of this research, the term 'raw data' refers to interview transcripts. Inductive analysis differs from deductive analysis which refers to "data analyses that set out to test whether data are consistent with prior assumptions, theories or hypotheses identified or constructed by an investigator" (Strauss & Corbin, 1998, p. 12).

As noted, a modified approach to inductive qualitative analysis is undertaken in this research. Following Locke (2002, p. 19), this study aims to undertake theory building that is fundamentally related to direct contact "with the social world, coupled with a rejection of a priori theoretical categories and propositions". For Miles and Huberman (1994, p. 1):

> [qualitative data are] a source of well-grounded, rich descriptions and explanations of processes in identifiable local contexts… can offer a perspective on chronological flow, and insight into the

> consequences of events, which can yield "fruitful explanations... good qualitative data are more likely to lead to serendipitous findings and to new integrations; they help researchers to get beyond initial conceptions and to generate or revise conceptual frameworks.

Following Thomas (2006, p. 239), the principles, or analytic strategies of the general inductive approach include the following:

1. Data analysis is guided by evaluation objectives, which identify domains and topics to be investigated. The analysis is carried out through multiple readings and interpretations of the raw data. The findings arise directly form the analysis of the raw data, not from a priori expectations or models. The evaluation objectives provide a focus or domain of relevance for conducting the analysis, not a set of expectations about the specific findings. In the case of this research, the evaluation objectives (and research questions) relate to the determinants of research productivity and the relationship between technological propensity and productivity.
2. The primary mode of analysis relates to the development of categories from the raw data into a model of framework. This model contains key themes and processes identified and constructed during the coding process.
3. The findings result from multiple interpretations made from the raw data by the evaluator who codes the data. Inevitably, the findings are shaped by the assumptions and experiences of the evaluators conducting the study and carrying out the data analyses. For the findings to be usable, the evaluator must make decisions about what is more important and less important in the data.
4. The trustworthiness of the findings derived from inductive analysis can be assessed using similar techniques to those that are used with other types of qualitative analysis.

The use of an inductive approach is consistent with the general patterns of qualitative data analysis described by Miles and Huberman (1994, p. 10), who describe three broad tasks of qualitative data analysis, including: i) data reduction, ii) data display and iii) conclusion drawing, or verification. A description of the verification of the qualitative research methodology follows.

3.4.1 Verification of the Qualitative Process

The following four criteria need to be met for qualitative research to be trustworthy (Guba, 1981, p. 79).

- Truth Value (Internal Validity): to establish confidence in the 'truth' of the findings. In this study, truth-value was attained through the strength of the linkages between quantitative and qualitative data.
- Applicability (External Validity/Generalisability): to determine the extent to which the findings are applicable in different contexts or in the case of other respondents. Selecting respondents from a diverse range of fields of study and universities strengthens the applicability of this study.
- Consistency (Reliability): to determine if the findings are replicable. Consistency in relationships (that emerge from the qualitative research) was obtained by selecting diverse respondents.
- Neutrality (Objectivity): to establish the extent to which the findings are free of researcher bias. Weber (1949, translated by Shils & Finch, 2017) suggests that all social research is inherently biased, and complete neutrality and objectivity are impossible to achieve since the values of the researcher and participants are always present. However, the use of mixed methods has been suggested as way to combat bias in that qualitative and quantitative methods may effectively 'cancel out' each other's bias (Creswell, 2003). Therefore, the use of a mixed methodology in this study supported neutrality.

These criteria relate to the 'rationalistic paradigm', which assumes that an underlying reality does exist and that the findings will converge on a "single reality" (Guba, 1981, p. 79). Truth value (internal validity) was ensured through the strength of linkages between the qualitative and quantitative data, since alternative explanations were excluded as the data was analysed (Guba & Lincoln, 1982). Applicability (generalisability) was attained using the theory development process (Guba, 1981; Guba & Lincoln, 1982; Lincoln, Lyham & Guba, 2011). Consistency was attained by tracking the research processes in that data records were maintained, and all processes were recorded. Objectivity was maintained throughout the entire research process by relating data to other data in a systematic process and ensuring that each

stage in the analysis was warranted (Guba, 1981; Lincoln, Lynham & Guba, 2011). The process of qualitative analysis is now discussed.

3.6 QUALITATIVE ANALYSIS

The following section provides an overview of the qualitative analysis undertaken in this research. A more detailed description of the process of coding is provided in section 3.5.3, below. The population, sample, instrument and methods of analysis for the qualitative research discussed first, as follows.

3.6.1 Population and Sample of the Qualitative Study

The population from which the qualitative research respondents were drawn consists of internationally recognised scientists, innovators and researchers from across the world; those at the forefront of research in their respective fields, and who have gained international recognition for their innovative work and breakthrough productivity. As such, these respondents were expected to exhibit high levels of Breakthrough Research Productivity (BRP). The objective of the qualitative portion of the research was to develop theory that related to the influence of the uptake of new technologies and methodologies (technological propensity) in relation to BRP as well as the human resources management determinants that may impact this relationship.

A maximum heterogeneity sampling technique was used to ensure a diverse set of respondents ranging from different fields of study. This sampling method is justified since any shared characteristics between fields of study will have more salience. To do so, lists of notable international scientific and technological award winners were compiled. These are listed in the Table 6 below.

Table 6: Qualitative Sample Awards

Prize/Award/Medal	Number of Laureates/Winners*	Sample Respondents	Notes
The Nobel Prize	664	3	Excluding the Nobel Prize for Peace and the Nobel Prize for Literature.
The Lasker Award	92	3	
The Wolf Prize	273	6	Excluding the Wolf Prize for Arts.
The Turing Award	64	2	
The Fields Medal	56	1	
The Einstein Prize and the Einstein Medal	37	3	Includes the Einstein Prize and the Einstein Medal.
The Shaw Prize	48	3	
The US National Medal of Science	586	8	Respondents from USA only.
The US National Medal of Technology and Innovation	98	1	Respondents from USA only.
The L'Oréal-UNSECO Award for Women in Science	337	2	All respondents in this category are female.
The Breakthrough Prize	34	3	Excluding prizes awarded to institutions, large teams, corporations and organisations.
The Kyoto Prize	73	1	Excluding Prizes awarded to institutions, large teams, corporations and organisations.
Other	N/A	2	Included the International Grand Prix Award and South African NRF A-Rating and used for Pilot study.
TOTAL	**1481**	**38***	

* Some respondents were recipients of more than one award. (for example, R05 received both The Nobel Prize and the Wolf Prize. R06 received both the Einstein Prize and the Shaw Prize)

Many of the prizes listed above are often awarded to institutions, corporations, large teams and organisations. These have been excluded from the sample. Many individuals have won multiple awards and have in some cases won the same award twice. Some prizes (such as the Nobel Prize) that include categories such as the arts, literature and peace have been excluded from the sample as winners in these categories cannot always be classified as scientists, academics, or researchers (Hall & Johnson, 2009). The category 'other' comprises two respondents who were interviewed for a pilot study. These respondents were selected using convenience sampling.

In total, the qualitative sampled comprised 30 respondents, ranging from several different prize-winner lists. Qualitative interviews took place telephonically or via instant video-conferencing (namely, Skype). For qualitative interviews, respondents were approached independently of their universities or institutional affiliations; contact details were acquired through public sources only (i.e. the Internet). Respondents from a broad range of areas of expertise were identified, thus ensuring heterogeneity (Pitard, 1993). According to precedent offered by qualitative analysis, statistical generalisability was not the goal of the qualitative process (Labuschagne, 2003; Brinkshaw, Brannen & Tung, 2011). A sample size of 30 was judged adequate for obtaining 'thick descriptions' of the relationships around research productivity (Miles & Huberman, 1994; Miles, Huberman & Saldana, 2014). An overview of the research instrument that was used for the qualitative portion of this research is provided as follows.

3.6.2 Qualitative Research Instrument: Interviews

A schedule of interview questions was composed by identifying dominant themes in the literature pertaining to the theoretical model under study. The interview consists of five inter-related questions about the theoretical constructs under study. These pertained to i) human capital investments; ii) personality characteristics; iii) motivational values; iv) work climate; and v) technological propensity, or the extent to which individuals take advantage of certain new technological opportunities. Questions relating to technological propensity comprised five sub-questions, each of which related to 6G innovation theory (Callaghan, 2014; 2015; 2016; 2017).

The full interview schedule is included in Appendix 8.3.3. Prior to the commencement of an interview, respondents were informed that the interview was expected to span between 30 to 45 minutes. Response times varied greatly, depending on the respondent. The shortest interview was completed in ten minutes and 15 seconds; the longest interview was completed in 61 minutes. The average time of completion for all 30 interviews was calculated to be 31 minutes. Interview transcripts are included in Appendix 8.7.

The interviews were semi-structured to allow for variations in questions probing for richer respondent output, variations in interview structure, and a free-flow of participant engagement (Wagner, et al., 2013). The interviews were also non-standardised to allow flexibility and

standardisation of meaning of questions, considering the research objectives (Britten, 1995; Brinkman, 2014). The non-standardised approach allowed for broad, open-ended questions, which yield greater levels of validity and reliability as well as richer answers from respondents (Brinkman, 2014).

Blanket emails detailing sample participation was sent to all potential qualitative respondents. Those who responded positively were contacted to arrange convenient dates and times for the interviews. The primary researcher took on the role as the interviewer for the qualitative portion of the research because the interviews required a high level of knowledge and understanding of the topic at hand. Interviews occurred both telephonically and via video-conference (e.g. Skype)

During interviews, respondents were asked a series of open-ended questions. Interviews were recorded using standard iOS recording software for iPhone SE, which was transcribed later. Interviews only proceeded after prior written consent of the respondents was obtained in the form of a signed participation information sheet. The participation information sheet also contained a statement that informed the respondent that the interview would be audio recorded, and thereafter transcribed. The participation information sheet is included in Appendix 8.3.1.1 The derivation of the questions included in the interview schedule is now discussed.

3.6.3 Derivation of Interview Schedule

The derivation of primary questions contained in the interview schedule are now briefly discussed, in relation to theory. The first of these questions is as follows.

> *Was there anything specific in your background, such as experience, education, training, that contributed to your breakthrough work? How do you think your prior experience contributed to your (biggest/major) breakthrough?*

This question was asked to investigate the extent of human capital investment effects on BRP. According to Becker (1962), the accumulation of education, training and experience may contribute to the appreciation of an individual over time, thereby positively influencing work performance, or in this case, work productivity. The next question was asked to determine human resources (HR) determinants of BRP.

Hypothetically, if you were an HR/hiring manager, looking for researchers who are able to produce research breakthroughs, what characteristics would you look for?

This question was asked to investigate the relationship between of personality, motivational values and work climate perceptions and BRP. Probing questions, which related more specifically to personality, motivational values and work climate perceptions were used to elicit richer responses. The relationship between technological propensity and BRP was also investigated qualitatively. This relationship was investigating by way of a series of interlinking questions, to determine the extent to which the adoption or use of certain new technological and methodological advancements (specifically, those which may offer significant economies of scale) may contribute to breakthrough research productivity. The questions related to technological propensity are as follows:

Do you think that journal publications that accept academic work in your field sufficiently promote innovative research in your field? Did you experience any type of resistance from the academic publishing system when trying to publish your breakthrough?

The management of scientific research is sometimes considered counter-productive. Do you think it is necessary, or possible to try to enhance the effectiveness/efficiency of scientific research, or to try accelerating the rate at which breakthrough innovations occur? And why/why not?

In our increasingly globalised world we often find that what once may have been smaller, localised problems have begun to spread on a more global basis. A prime example is the Ebola outbreak of 2014, which quickly became a worldwide phenomenon. What is science and scientists' and researchers' role in addressing these types of global problems, which – like in the case of Ebola – seem to occur almost in real-time?

There's been a recent trend in the use of open innovation; obtaining data from large numbers of people spread across different geographical locations through the Internet and social media and smart technology. This has become very popular in health/medical research and is known as participative science. What are your thoughts on using these types of technologies to gather data in your field?

A lot of research faces budget constraints. Can you think of any way to streamline research funding or think of alternate methods of research funding?

Each of the above question relates to a different element, or construct related to technological propensity, including i) the state of academic journal publication, ii) the management of innovation, iii) real-time problem solving, iv) crowdsourcing and v) crowdfunding, respectively. Having concluded discussion of the derivation of the interview schedule, the process of qualitative data coding and analysis is now considered.

3.6.4 Coding and Analysis

Qualitative data collection commenced in March 2017 and concluded in July 2017. All interviews were conducted telephonically or via video-conference (e.g. Skype). A process of inductive thematic content analysis was used to analyse qualitative data. For Elo and Kyngas (2008), the outcome of an inductive analysis is the development of categories into a model or framework that summarises the raw data and conveys key themes and processes. The categories resulting from the coding, which are the core of inductive analysis, potentially have 5 key features (Thomas, 2006, p. 241):

- Category label: a word or short phrase used to refer to the category. The label often carries inherent meanings that may or may not reflect the specific features of the category.
- Category description: a description of the meaning of the category, including key characteristics, scope and limitations.
- Text or data associated with the category: examples of text coded into the category that illustrate meanings, associations and perspectives associated with the category
- Links: each category may have links or relationships with other categories. In a hierarchical category system. These links may indicate superordinate, parallel and subordinate categories (also referred to as ‘parent’, ‘sibling’ or ‘child’ relationships). Links are likely to be based on commonalities in meanings between categories or assumed causal relationships.
- The type of model in which the category is embedded: the category system may be subsequently incorporated in a model, theory, or framework. Such frameworks include an open network, a temporal sequence and a causal network. To be consistent with the inductive process, such models or frameworks represent an end point of the inductive

analysis. They are not set up prior to the analysis. It is also possible that a category may not be embedded in any model or framework.

The process of inductive coding commenced with the close reading of text and consideration of the multiple meanings that were inherent in the text (Miles & Huberman, 1994; Miles, Huberman & Saldana, 2014). Text segments that contained 'meaningful units' were then identified and assigned to labelled categories (Miles & Huberman, 1994; Elo & Kyngas, 2008; Miles, Huberman & Saldana, 2014). Each labelled category was accompanied by a 'memo', which included references to associations, links and implications (Thomas, 2006), or in other words, a brief description of the labelled category. Categories containing similar underlying themes or sub-themes were linked, resulting in a hierarchical network of interrelationships amongst categories. Following both Thomas (2006) and Miles, Huberman and Saldana (2014), the following procedure of 'inductive coding' was used for the inductive analysis of qualitative data:

1. Preparation of raw files (data cleaning): raw data (interview audio recordings) were transcribed into a common format (i.e. interview transcripts)
2. Close reading of text: interview transcripts were read several times.
3. Creation of categories: categories were identified and defined. Text segments, or important and relevant quotes from interview transcripts were assigned to different categories. This stage of analysis resulted in roughly 30 different categories.
4. Reduce overlap and redundancy: categories and text segments considered redundant or irrelevant the objectives of the study were removed. A process of continual revision and refinement was follows to construct an interlinking and hierarchical 'category system' or network of categories and sub-categories. Each category contained relevant text segments from interview transcripts, including contradictory points of view and new insights as well as links to other sub-categories

Codes were derived from interview transcripts. Codes were then grouped into categories, or themes, as per the methods defined by Miles, Huberman and Saldana (2014) and Thomas (2006), by using both inferential and descriptive codes. Coding resulted in the creation of the 'concept theme', which is the unit of analysis for the study (Bazeley, 2009; Miles, Huberman & Saldana, 2014). Thematic content analysis was used for the reporting and discussion of results (Smith, 1992; Anderson, 2007). Interview questions were constructed to allow for

sufficient probing and further exploration of responses in a flexible manner, as prescribed by Corbin and Strauss (2014). To test theory derived from the literature, the mixed methods approach, which uses both qualitative and quantitative methods (Creswell, 2003) was employed in the hope of arriving at a comprehensive perspective and at a holistic synthesis. During interviews, responses were recorded and thereafter transcribed, coded and analysed.

An attempt was made to derive codes from the data that were at the individual level of analysis. The coding list was amended and adjusted iteratively in an inductive manner as the analysis progressed (Miles & Huberman, 1994; Miles, Huberman & Saldana 2014; Thomas, 2006). The codes were thereafter developed into themes (Anderson, 2007). The list of final codes used in the process are reported in tabulated form in Chapter 4. Codes at the level of themes were retained for analysis. Each of these tabulated lists indicate the following: i) the general code of the category, ii) the general aspects or descriptive name of the category, and iii) the sub-themes which fell within each category (Thomas, 2006). Although the analysis developed its own structure, the scope of this research was limited to the relationships around technological propensity and BRP and therefore only themes relevant to the research questions were reported and discussed. Thematic content analysis was the final form of analysis adopted for the reporting and discussion of the results.

Following a process of data coding, a second set of codes was produced which was then further processed as pattern coding to: i) reduce the data into core analytic units, ii) facilitate the development of a cognitive map or "more integrative schema for understanding local incidents and interactions", and (iii) for "surfacing common themes and directional processes" (Miles & Huberman, 1994, p. 69). The pattern coding process formed the basis of discussion in the final analysis as relationships were discussed in terms of patterns (themes) in the writing up phase. This research limited the scope of the analysis to a focus on data collection at the level of 'consequences' (Miles, Huberman & Saldana 2014) due to the formulation of qualitative questions about the 'causes' of research productivity, or what factors contributed to technological propensity and BRP. As such, only the relationships relevant to constraints and the enablement of research productivity were reported and analysed.

Following Glaser (1992), interview questions were used in a flexible manner to probe and explore responses from respondents. The unit of analysis used was the 'concept', in the form of a theme, either articulated as a short phrase or as a group of sentences. Pattern coding formed

the rationale for the allocation of data into families of data (Q analysis), or families of themes, following the prescriptions of Miles, Huberman & Saldana (2014). This process is analogous to the use of statistical clustering techniques and methods such as statistical factor analysis (Miles, Huberman, 1994; Kothari, 2004).

The patterns of relationship that related to each of the overall conceptual categories were then analysed. Relationships were analysed and an attempt was made to gain an understanding of whether the factors in the quantitative analysis were justified for inclusion, by incorporating data from a wide and diverse set of respondents. It was found that these factors were indeed justified, since very similar themes emerged from the process of qualitative analysis.

Once the process of qualitative coding was complete, a process of proposition derivation commenced. Testable propositions were derived from the qualitative analysis (Bulmer, 1979; Locke, 2002). The combination of these propositions forms the basis of a 'story', that has emerged from the data and helps to guide the research process. For Locke (2002, p. 38), at this stage, relationships between the developed theoretical framework and other theory are typically drawn out, and the extent to which the developed theoretical framework "confirms, challenges, or extends existing ways of conceptualising the phenomena of interest" is established. In this way, a point of theoretical saturation is reached (Locke, 2002; Francis, et al., 2010). Upon reaching theoretical saturation, the relationships between categories and sub-categories was analysed and propositions were derived. A model of propositions was composed and contrasted to the theoretical model derived from the literature. The quantitative research methodology is now discussed.

3.7 QUANTITATIVE RESEARCH METHODOLOGY

The following sections relate to the processes applied in the quantitative portion of this research. The research design, scope of the study, population and sample, methodology and levels of analysis are introduced. After this, issues relating to the data collection process, the sampling process, the sample size calculation, the sampling protocol, the interview process, and reliability and validity are considered. The hypotheses are then introduced, and the scale measures and statistical methods used to test each are also examined. The chapter then proceeds with a consideration of ethical issues and the limitations associated with the research. It is stressed once again that all three studies were undertaken concurrently.

The objective of the qualitative research is to provide a validation, or justification for the choice of variables tested quantitatively. For Drasgow & Schmidt (2002, p.4) "more sophisticated tools should never be used when a simple mean, standard deviation, frequency table, correlation, regression analysis, or plot of the data is sufficient to answer a research question". The research followed this perspective and used qualitative analysis in addition to quantitative analysis to provide a holistic analysis to answer the research questions. Both analyses were conducted concurrently. The population and sample of the quantitative study is now considered.

3.7.1 Population and Sample of the Quantitative Study

The quantitative population and sample comprised two sub-samples; the academic sub sample and the crowd-worker sub-sample. Each of these is discussed in this section. This research follows precedent of previous, cross-sectional studies that investigate academic researcher productivity (previously referenced in Chapter 2). In a study on the relationship between age and research productivity, Levin and Stephan (1991) use a sample of 903 scientists. Long (1992) examined gender differences in scientific productivity by surveying a sample size of 1059 respondents. Dietz and Bozeman (2005) investigate the association between experience and productivity using a sample size of 913 academics. Sooryamoorthy and Shrum (2007) surveyed 275 South African scientists in a study of South African research collaboration and publication. Ynalvez and Shrum (2011) use a sample of 312 scientists in a study of publication productivity in developing countries.

This research also follows the precedent of previous studies that have used Amazon's MTurk to collect survey data. One of the benefits of MTurk is the high speed at which large datasets can be gathered. MTurk use in scientific research has increased significantly. "In 2011… just 61 studies using MTurk were published; last year [2015] the number topped 1200" (Bohannon, 2016, p. 1). There are numerous examples of social science research projects that have used MTurk to collect data. Heen, Lieberman and Miethe (2014) contrast different online survey hosting websites, sampling a total of 304 MTurkers. Harrison-Walker (2015) use a sample of 600 MTurkers to test the difference between lab participants and MTurkers in psychology research. Stothart, Boot and Simons (2015) sample 515 MTurkers to investigate 'cognitive

ageing'. MTurk use in academic research has expanded into different areas of social science including psychology, health and economics research (Bohannon, 2016).

In a process of comprehensive purposive sampling for both sub-samples, all potential respondents within the population were used to fill an approximate sample size, conservatively and broadly based on a sample size calculation to achieve a $p < .001$ level of significance, and previous studies of a similar nature, as discussed above. According to Field (2012), when the population is unknown, the sample size can be derived by computing the minimum sample size required for accuracy in estimating proportions. This is done by considering the standard normal deviation, set at a 95% confidence level. Smith (2013) suggests the use of the following formula to determine sample size:

$$n = z^2 (\sigma) (1- \sigma)/ (\text{margin of error})^2$$

Where:
z = standard normal deviation set at 95% confidence level
σ = standard deviation

The sample size calculation was performed. It is argued that the use of this calculation provides ground to determine a sample size large enough to achieve accurate statistical outcomes (Marsh, Balla & McDonald, 1988; Smith, 2013). In other words, the sample size calculation is used to determine a sample size large enough to be sufficiently sensitive to detect significant differences at the 5% level of significance (Field, 2012; Smith, 2013).

The quantitative sample is split into two sub-samples. The first quantitative sub-sample consists of 457 academic researchers in South African tertiary institutions and universities. This is referred to as the 'academic researcher (AR) sample' and draws from an estimated 18 500 active academic researchers in South Africa (Center for Higher Education Trust (CHET), 2015). Of the nine South African universities sampled, this sample size equates to roughly 5.7% of the population. The second sub-sample comprises 569 'crowd-workers', or individuals from across the world that use Amazon's Mechanical Turk, or MTurk, which claims a rough estimate of "500 0000 workers from 190 countries" (MTurk, 2017, p.1). This number however, is debated. In a 3-year study investigating the effectiveness of MTurk research, Stewart (2015, p. 479) surmises that "the number of unique people [MTurk subjects] came to only 30,000…

the true number of MTurkers that are willing to take part in an experiment at any one time is only about 7300." Following Stewart, the crowd-worker sample equates to roughly to 7.8% of the population. Each of the sub-samples are now discussed.

3.7.1.1 Academic Researcher (AR) Population and Sample

A process of comprehensive purposive sampling, in which all potential respondents within the population were invited to participate, was undertaken. The academic sample was sampled via electronic means (e-mail) and consisted of respondents from a broad range of fields of study, so as to ensure sample representation. As of 2015, the estimated total population of active academic researchers in South Africa is approximately 18 567 (CHET, 2015). It is acknowledged that this number is outdated but more recent statistics are not yet available (CHET, 2017). The total population of an estimated 7 595 respondents is much smaller from the nine universities that granted permission to the researcher. The table below depicts the number of estimated permanent academic staff, per university.

Table 7: Number of permanent academic staff, per South African university (CHET, 2015)

	University	**Number of Permanent Academic Staff (2015)**
1	The University of Witwatersrand	1 144
2	The University of Cape Town	1 179
3	The University of Pretoria	1 192
4	Nelson Mandela Metropolitan University	624
5	The University of Kwa-Zulu Natal	1 341
6	Cape Peninsula University of Technology (CPUT)	807
7	Rhodes University	318
8	University of Fort Hare	345
9	University of Western Cape (UWC)	645
	Total	**7 595**

For the academic researcher sample, n (sample size) = 457. The standard deviation of the sample is used as a proxy of the standard deviation of the population. A sample size of 457 is considered appropriate to obtain a significant effect for the tested variables. A significance level of five percent ($\propto = 5$) was used as the point of probability of a Type I error (Edwards, 1984). A total of 550 electronic questionnaires were submitted. Of these, 93 questionnaires were incomplete and were hence excluded from the analysis, bringing the total sample to 457

respondents. This sample size is deemed large enough for the purposes of this research (Field, 2012).

3.7.1.2 Crowd-worker (CW) Population and Sample

The second quantitative sub-sample consists of 569 crowd-workers. Amazon's Mechanical Turk, (or MTurk), a crowdsourcing internet marketplace which provides a platform for widely distributed Human Intelligence Tasks (HITs) was used to gather data (MTurk, 2017). Given the nature of the research question, MTurk was considered particularly suitable for this research. Estimates of the number of MTurk users is almost impossible to discern (Dholakia, 2017), however, MTurk claims a rough estimate of "500 0000 workers from 190 countries" (MTurk, 2017, p. 1). The viability (Bahrend et al., 2011), reliability (Chandler et al., 2014) and validity (Casler et al., 2013) of MTurk have been thoroughly investigated. MTurk has been found to produce similar results to those of traditional sampling in behavioural research. For Casler, et al. (2013, p. 2156), "MTurk participants [are] significantly more socio-economically and ethnically diverse, yet test results were indistinguishable." Further, according to Goodman, et al. (2013, p. 213), "MTurk participants produce reliable results … MTurk offers a highly valuable opportunity for data collection."

Convenience sampling was used for the crowd-worker sample. It is acknowledged that convenience sampling implies that the generalisation of results may be restricted (Polit & Beck, 2010). An MTurk account was created and an HIT entitled 'Answer a survey about MTurk Productivity' was posted to the MTurk dashboard, which immediately became available to MTurk workers (MTurkers). MTurkers that selected the task (i.e. agreed to partake) were redirected to the online questionnaire. Upon completion of the questionnaire, the MTurkers were asked to provide their MTurk ID numbers. MTurk ID numbers were cross-referenced with MTurk's database of completed HITs to make sure all those MTurkers that completed the questionnaire were paid. A total of 617 questionnaires were collected. There were 48 incomplete questionnaires which were excluded from the analysis, bringing the total sample size to 569 respondents. This sample size was deemed large enough for this research. For the crowd-worker sample, n (sample size) = 569. The standard deviation of the sample is used as a proxy of the standard deviation of the population. This sample size considered appropriate to obtain a significant effect for the tested variables. A significance level of five percent ($\propto = 5$)

was used as the point of probability of a Type I error (Edwards, 1984). Missing quantitative data is discussed next.

3.7.2 Missing Data

According to Allison (2001), there are three types of missing data. These include i) Missing Completely at Random (MCAR), ii) Missing at Random (MAR) and iii) Missing Not at Random (MNAR). Item non-response (or, missing values) may occur when respondents do not respond to certain questions due to fatigue, stress or lack of knowledge (Graham, 2009). MCAR refers to cases where missing values are randomly distributed across all observations. MAR refers to cases where missing values are not randomly distributed across observations but are distributed within one or more sub-samples. MNAR refers to cases that are neither MCAR nor MAR (Glas & Pimental, 2008). For Allison (2001, p. 171), missing values can be handled by either "leaving the data" or "conducting data imputation to replace them." If the number of cases of missing values is extremely small (i.e. less than 5%), then these values may be omitted from further analysis, using either list-wise or pair-wise deletion (Dong & Peng, 2013). A list-wise deletion is a method in which an entire record is excluded from analysis if any single variable is missing. A pair-wise deletion is a method in which cases that contain some missing data are used for analysis. A pair-wise deletion procedure cannot include a particular variable when it has a missing value, but it can still use the case when analysing other variables with non-missing values. The use of either list-wise or pair-wise deletion depends on the type of analysis (Allison, 2001). In the case of multivariate analysis, missing data can be replaced with mean values (Dong & Peng, 2013). In the case of univariate analysis however, a process known as imputation is required to decrease the amount of bias in the data (Rubin, 1987; Rubin 1996). However, imputation is only required if values are MAR (Allison, 2001; Graham, 2009). To assess missing data, a data partition was conducted. This process partitions the data into two parts: one set containing missing values and the other containing non-missing values. Thereafter, a t-test of mean-difference was carried out to identify the existence of any differences in the sample between the two data sets (Allison, 2001).

In both the academic researcher and crowd-worker quantitative samples, it was discovered that the data were MCAR, but also that the total missing data accounted for less than 5% of the total sample. This includes scale items, categorical, nominal and continuous variables. This means that the probability of missing data of dependent variables is unrelated to other

independent variables, as well as the dependent variable itself (Graham, 2009). Therefore, a pair-wise deletion of missing value cases was implemented (Allison, 2001; Graham, 2009; Dong & Peng, 2013). The qualitative research instrument and data collection procedure is discussed next.

3.7.3 Quantitative Research Instrument and Data Collection Procedures

Questionnaires hosted online on surveymonkey.com were distributed to both the academic research and crowd-worker sub-samples. For academic researchers, questionnaires were distributed via e-mail. For crowd-workers, questionnaires were made available via Amazon's Mechanical Turk. Both of these processes are discussed in this section.

3.7.3.1 Questionnaires

Questionnaires were derived primarily from literature. The academic researcher sub-sample questionnaire was administered to over 5 000 academic researchers across South Africa, at the institutions as listed above. In total, 550 respondents responded to the questionnaire, although only 457 respondents completed the questionnaire fully. Those questionnaires that were not completed were excluded from the analysis. The crowd-worker sub-sample questionnaire was posted online, on Amazon's MTurk platform. In total, 617 MTurk users attempted to complete the questionnaire. Of these, 48 questionnaires were incomplete and therefore excluded from further analysis, bringing the total sample size to 569 respondents. Two similar questionnaires were used to collect data from the quantitative samples, each of which contained five sections.

Section A in both questionnaires was designed to capture respondent's biographical information, human capital investments (HCI) and level of productivity. This section consisted of 11 questions for the academic sample and 12 questions for the crowd-worker sample, all of which required one-word answers or ticking an appropriate box. Questions relating to biographical information asked respondents for their age, gender, nationality and first language, as per precedent in similar studies of productivity (Levin & Stephan, 1991, Long, 1992). Questions relating to HCI were included to assess the impact of experience and education (Becker, 1962; Black & Lynch 1995). These questions asked academic researcher respondents for their 'years of experience as an academic researcher'. Crowd-workers were asked to indicate their level of formal education received. In terms of productivity, academic

researcher respondents were asked for the total number of journal articles they had had published over the course of their careers, following the precedent of previous studies on research productivity (Sooryamoorthy & Shrum, 2007; Ynalvez & Shrum, 2011). Crowd-workers were asked for the total number of MTurk HITs they had successfully completed over the course of their MTurk careers.

Section B measured personality using an abbreviated form of Costa and McCrae's (1992) NEO-FFI inventory, namely Gosling, Rentfrow and Swann's (2003) Ten Item Personality Inventory (TIPI), which was further modified to include 25 items. Section C contained two versions of Schwartz's PVQ (Portrait Values Questionnaire), one for male respondents and one for female respondents (Schwartz, 2012) and which comprised of 23 items. Section D included a modified version of Patterson, et al.'s (2005) innovative climate inventory which includes 25 items and was only included in the academic researcher questionnaire, since this question was not applicable to crowd-workers, most of whom work from home (Goodman et al., 2013). Section E contained the 20-item technological propensity scale, which was derived from the literature. Finally, Section F contained a 4-item Brief Social Desirability Scale (BSDS) (Haghighat, 2007).

The academic sample questionnaire differed from the crowd-worker questionnaire in that crowd-worker's productivity (CWP) was measured as a ratio of total of Human Intelligence Tasks (HITs) completed on MTurk over the number of years the respondent has been an MTurk user. Moreover, the crowd-worker version of the questionnaire contained a different version of the technological propensity scale, adapted to suit the variability in professions of crowd-workers. The full versions of both questionnaires are included in Appendix 8.4.

3.7.2.2 Data Collection Process

A full proposal to conduct the research in question was submitted to the ethics committee of the University of Witwatersrand in February 2017 and ethics approval was granted in March 2017. The research proposal outlined a projected research objective and research process that would be adhered to over the course of the research according to the stipulations specified by the School of Economics and Business Science at The University of Witwatersrand. The requirements of relevance and informed consent (Anastasi, 1990) were used to guide the design of the instrument. Consent forms were used to ensure that anonymity and confidentiality were

guaranteed to respondents. Cover letters and consent forms were attached to the survey instrument. These are included in Appendix 8.4.

The sampling protocol stipulates the use of standardised processes (Anastasi, 1990), so that no extraneous variance is introduced into the process and any unusual conditions with the potential to influence responses were documented (Anastasi, 1990). The instrument was piloted, and the items were developed in such a way as to enhance clarity and simplicity and gather information about reliability and validity. The principles of reliability and validity were also used as a guide for the data collection and data analysis processes. Precedent was followed in each step of the data collection process. Scales were used that had been found to be reliable and valid in other contexts. The sampling protocol dictated that these scales needed to be tested in piloting. Precedence from previous research was also strictly followed to ensure that the sampling process did not introduce extraneous variance. This research extends previous research into a new context and the processes were carefully considered to maintain the integrity of the research. Questions included in the instruments were phrased in a neutral fashion to avoid social desirability bias (Murphy & Davidshofer, 2005). Furthermore, a brief social desirability scale (Haghighat, 2007) was included in the research instrument. Content, construct, face and criterion validity were ensured throughout the sampling and instrument design stages. Information relating to convergent and discriminant validity was noted at all stages of the process. As per precedent, confidence testing was performed using the five percent level of required significance. Respect for the wishes of individuals approached was an important aspect of the sampling protocol, and any indication of refusal was unconditionally respected. The process of data collection for both sub samples is now discussed.

3.7.2.2.1 Academic Researcher Sample

Prior to commencement of data collection, permission was obtained from relevant universities and institutions. These generally required proof of registration, ethical clearance, a full research proposal, and samples of the intended questionnaire. All certificates of permission are included in Appendix 8.8. All nine universities that cleared the research required no changes to be made to the questionnaire. The list of South African universities that agreed to partake in this research is listed in Table 7.

Once permissions were obtained, data collection commenced. Data collection commenced in March 2017 and concluded in January 2018. Blanket e-mails detailing sample participation were sent to all potential academic researcher sample quantitative respondents. All relevant details were enclosed, including a brief description of the research to be conducted, the expected amount of time for completion, a covering letter with the contact details of the researcher and the researcher's supervisor and a full explanation of the research procedure as well as an invitation to participate or decline if the respondent so wished. Both a cover letter and a consent form were attached to the research instrument (questionnaire) to guarantee anonymity and confidentiality for all respondents. E-mails also contained a web-link to the questionnaire.

All blanket emails contained a consent form with provision for digital signatures of respondent and researcher as well as acknowledgement of the participatory regulations and copies of the Ethics Committee's clearance certificate. Once respondents opened the web-link of the email, the first page of the questionnaire became available. Brief descriptions of the study, expected completion time, consent forms, cover letters and the researcher's details were all included as attachments in the email, as was ethical clearance from the University of Witwatersrand (of the researcher) and ethical clearance from the university, by which the respondent in question was employed (see Appendix 8.4).

3.7.2.2.2 Crowd-worker Sample

The crowd-worker questionnaire was posted on Amazon's Mechanical Turk in April 2017. 617 completed questionnaires were gathered in the space of two hours. MTurk seekers are required to pay MTurk workers for HITs, based on the estimated time to complete the task. Given that the questionnaire took between 10 to 15 minutes to complete during pilot testing, MTurk users were paid US $0.50 per completed questionnaire. This figure was based on MTurk's user guidelines (MTurk, 2017).

3.7.3 Scope of the Study

The scope of the quantitative study was chosen to reflect the design of an appropriate test for 6G innovation theory. The scope is limited according to its focus on the relationship between technological propensity and productivity, and the HRM determinants which may impact this

relationship. These include i) personality, ii) motivational values, iii) work climate perceptions and iv) human capital investments. The scope is also limited in terms of its measures of productivity. This measure, for academic researchers, was defined by an aggregate measure of local Department of Higher Education and Training (DOHET), International Scientific Index (ISI), International Bibliography of Social Sciences (IBSS), and Scopus accredited journal article publications. This measure excluded measures of supervisory productivity, conference proceedings and presentations as well as text-book and academic book publications. The aggregated measure of productivity was used as an index of gross productivity, irrespective of the quality of the work. A similar limitation applies to the measurement of crowd-work productivity, which included the number of total MTurk HITs completed, irrespective of the quality of the work. The qualitative research was limited to individuals who have been awarded a prize for contributions to their field of expertise. The data collection and analysis phases were firmly guided by the principles of reliability and validity. Care was taken to phrase questions neutrally, to avoid social desirability bias (Murphy & Davidshofer, 2005).

3.7.4 Reliability

A fundamental requirement of a measure is its ability to produce scores that are consistent, or to "at least assign scores in a consistent fashion" (Murphy & Davidshofer, 2005, p. 79). Reliability is therefore the consistency of a measure "of a concept", and a reliable measure needs to display stability, internal reliability and inter-observer consistency (Bryman, 2004, p. 71). Care was taken to ensure the consistency of measures used in the research. For Murphy (2009), responses contain both true score values as well as random errors of measurement. Error can also be systematic and can arise from inconsistency in measurement. The sources of variability most relevant to a study should inform the use of tests of reliability (Meeker & Escobar, 2014). The measures that were used in this research all displayed stability, inter-reliability and inter-observer consistency (Bryman, 2004) to account for true scores as well as random errors of measurement (Murphy & Davidshofer, 2005; Gujarati, 2014). Chronbach's Alpha tests of reliability were used in order to assure internal consistencies. This ensures reliable measures that are stable and internally reliable (Bryman, 2004; Gujarati, 2014). The results of these reliability tests are reported later in this chapter. The considerations of validity are described in the next section.

3.7.5 Validity

Validity, or the extent to which the measures in question "actually do measure what it purports to measure" (Bryman, 2004) was ensured throughout. Any information relating to convergent and discriminant validity was carefully noted. Pilot tests were conducted to ensure validity. The several different types of validity were all pursued thoroughly. These include:

- Content validity: the extent to which the item sufficiently covers the area of study (Bryman, 2004). This is ensured by making sure the items of the question correctly sample what is meant to be sampled.
- Construct validity: the assurance that convergent and discriminant validity is held (Campbell & Fisk, 1959). This is ensured by conducting exploratory factor analyses.
- Face validity: the extent to which a measure appears to measure what it is supposed to measure (Bryman, 2004) is ensured by using cover letters and consent forms to all participants.
- Criterion validity: the extent to which a measure can predict performance (Bryman, 2004) is ensured by establishing whether a tool (e.g. questionnaire) can be compared to other similar validated measures of the same concept or phenomenon.

Having reviewed the qualitative research methodology, the quantitative measures that are used in this research are now considered.

3.8 QUANTITATIVE MEASURES

The quantitative measures included in the questionnaires are now discussed. These include the measures of productivity, human capital investments (HCI), personality, motivational values, work climate perceptions and technological propensity. The scales used in this research were carefully developed, with most of the constructs derived from previous research. Anonymity and confidentiality were stressed to ensure lower levels of bias from respondents. In the case of the measurement of items, continuous items were, as much as possible, designed to meet the requirements of ratio data, or where necessary, interval data (Stevens, 1946). Items were however, used to sample data in each of the different forms: nominal, ordinal, interval and ratio data, where each form was appropriate (Stevens, 1946). Each form of data was identified and

the assumptions of each were checked. The measurement of the dependent variable is now discussed.

3.8.1 Measure of the dependent variable: Productivity

The measurements of productivity used in this research differ according to sample. In Study 1, which samples notable scientific award-winners from across the world, productivity is related to the production of 'breakthroughs' or radical innovations. In Study 2, the quantitative academic research sample, productivity was measured by an aggregate total of journal article publications over time. In Study 3, the quantitative crowd-worker sample, productivity was measured by an aggregate total of completed MTurk projects (HITs) over time. These measures of productivity are illustrated in Figure 12 below, which depicts these three levels of productivity. On one extreme end of the spectrum is breakthrough research productivity, which relates to the production of breakthrough, innovative output, but which occurs slowly and inefficiently. At the other extreme end of the spectrum is crowd-work productivity which occurs with speed and efficiency but does not produce breakthrough, innovative outputs. At the center of the spectrum lies academic research productivity (measured by an aggregate of journal article publications). This research seeks to investigate ways to stretch academic research productivity to both ends of the spectrum, so as to produce academic research output that is both highly innovative and highly efficiently produced.

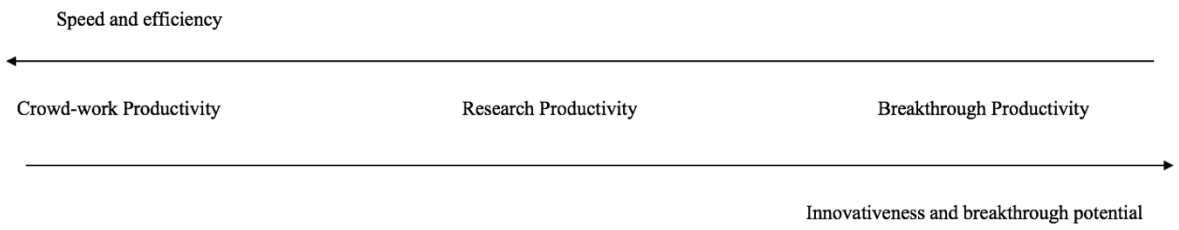


Figure 12: Measures of Productivity

Measures of research productivity have differed, according to past research. For Rachal, Shelley and David (2008), the use of journal publication productivity is considered a suitable measure of academic productivity because it can capture quality of research productivity. Peer review processes are used to determine acceptance and publication of journal articles, particularly in the case of journals with high impact factors. Impact factors are metrics that

reflect the average number of citations to articles published in research journals (Amin & Mabe, 2004).

For the academic researcher sub-sample, research productivity was measured by an aggregate total of peer-reviewed local and internationally accredited journal article publications, since these are both units that have a similarity of being a quantity-based measures. The exclusion of other productivity measures in the total productivity measure is justified by theory (Rachal, Shelly & David, 2008; Emrouznejad, Parker & Tavares, 2008). This measure was divided by the number of years of experience as an academic researcher, creating a research productivity ratio (total journal articles over years of experience as an academic researcher). It has been suggested that academic researchers may be at the mercy of the 'non-innovativeness' of journal publications (Campanario, 2009, Bornman, et al., 2010), where measures such as supervisory productivity, conference presentations and book publications are not subject to the same level of stringency (or, 'gatekeeping' effects) and hence may not represent a true reflection of productivity. For this reason, only journal publications are used as a measurement of productivity. For the crowd-worker sub-sample, crowd-worker productivity (CWP) was measured by an aggregate total of MTurk HITs (Human Intelligence Tasks) completed over the number of years the respondent has been an MTurk user, creating a ratio of crowd-work productivity.

3.8.2 Human Capital Investments (HCI)

Following Becker (1962), human capital investments (HCI) were measured by a combination of three measurements including years of education received, years of experience and years of experience in the respondents' primary field (whether as an academic, or other). Respondents were asked to provide biographical details including i) nationality, ii) first language, iii) marital status, and iv) number of children supported in family. The potential effects of these human capital variables may act as a detriment to productivity (Black & Lynch, 1995) and were therefore used as covariates during regression testing. HCI was measured in Section A of the questionnaire.

3.8.3 Modified Ten-Item Personality Inventory (TIPI)

This research assessed personality by making use of a brief measure of the Big Five personality traits, the Ten-Item Personality Inventory (TIPI) (Gosling et al., 2003). The most commonly used Big Five personality measures contain upwards of 50 scale items (Costa & McCrae 1999; John & Srivastava, 1999). Considering low response rates and the lengths of other scales in the questionnaire, it was deemed appropriate to use a shorter and quicker measure of personality. For Gosling et al., (2003, p. 504):

> The [TIPI] reached adequate levels in terms of a) convergence with widely used Big-Five measures in self, observer and peer reports, b) test-retest reliability, c) patterns of predicted external correlates and d) convergence between self and observer ratings.

The Big Five framework, comprising five broad personality factors, has become the most widely used and extensive research model of personality (Costa & McCrae, 1992: John & Srivastava, 1999), although it has not been universally accepted (Gosling et al., 2003). The most comprehensive Big Five measurement instrument is Costa and McCrae's (1992) 240-item NEO Personality Inventory, Revised (NEO-PI-R). There also exists a 60-item version of this scale (Costa & McCrae, 1992), a 44-item version (John & Srivastava, 1999), a 100-item version (Goldberg, 1992) and a 40-item version (Saucier, 1994).

Gosling et al., (2003) evaluate a 10-item measure of the Big Five, termed the 'Ten-Item Personality Inventory' (TIPI) and find that although somewhat inferior to the standard Big-Five instruments mentioned above, the TIPI reaches adequate levels in convergent and discriminant validity, test-retest reliability, patterns of external correlates and convergence between self and observer ratings (Gosling et al., 2003). Although not as comprehensive as larger inventories of personality, Gosling et al., (2003) note that short instruments can be useful tools when, i) time and resources are short, or ii) personality is not the primary topic of interest, as is the case in this research. For Gosling et al., (2003), internal consistencies for the TIPI were reported to be low but sufficient; Extraversion =.68, Agreeableness = .40, Conscientiousness = .50, Neuroticism = .73 and Openness to Experience = .45. While these internal consistencies where shown to be sufficient, it was noted that they could potentially be improved. The TIPI was augmented by adding an additional 15 scale items, making for a total of 25 items, with improved internal consistencies. New items were adapted from Costa and

McCrae's (1992) q-sort items relating to the Big Five Personality traits. Respondents are asked to answer, 'I see myself as…" and rank themselves on a scale of 1 to 6. Thus, the scale consists of 5 constructs, each measured with five 6-point Likert Scale questions ranging from 'very much like me' (1) to 'not at all like me' (6). The modified version of the TIPI scale is depicted in Table 8, below. Reversed items are denoted by an [R].

Table 8: Modified Ten-Item Personality Inventory (TIPI)

Construct					
Extroversion	Extroverted, enthusiastic	Reserved, quiet [R]*	Outgoing, talkative	Introverted, shy [R]	Active, assertive
Agreeableness	Critical, quarrelsome [R]*	Sympathetic, warm	untrusting, suspicious [R]	Forgiving, generous	appreciative, grateful
Conscientiousness	Dependable, self-disciplined	Disorganized, careless [R]	Efficient, organised	extravagant, self-indulgent [R]	reliable, responsible
Neuroticism	Anxious, easily upset	Calm, emotionally stable [R]	Tense, worrying	Confident, thick-skinned [R]	Self-conscience, vulnerable
Openness to Experience	Open to new experiences, complex	Conventional, uncreative [R]	Curious, imaginative	Conservative, orthodox [R]	Artistic, creative

*Reversed items are denoted by [R]

3.8.4 The Portrait Values Questionnaire (PVQ)

Schwartz's (2012) Portrait Values Questionnaire (PVQ) contains 21 items which correspond to ten lower-order human values and four broader 'higher-order values' (Schwartz, 1992, 2006a). According to Schwartz (2012), the PVQ typically does not use alpha scores since items are constructed from theory. However, internal consistencies scores for the four higher-order values of the PVQ have been reported: openness to change = .75, conservation - .75, self-transcendence = .74 and self-enhancement: .81 (Schwartz, 2012).

Motivational Values are measured in Section C (see Appendix 8.4.). The standard form of the PVQ uses short verbal portraits which are gender-matched with the respondent. Each portrait describes a person's goals, aspirations or wishes that point implicitly to the importance of a value. For each portrait, the respondent's answer to: 'How much like you is this person?' ranges

from ‘very much like me’ to ‘not at all like me’. As the topic of investigation is presented using a 5-point Likert Scale (Schwartz, 2012) it is argued that this method of data collection is effective in that the portraits capture the respondent’s values without explicitly identifying values. The universal applicability of the PVQ across multiple contexts (Schwartz, 2012) justifies its use for both the academic sample and the crowd- worker sample. It has also been tested in the South African context (Schwartz, 2007) and has been found to be suitable for a South African sample.

The Schwartz values orientation items were used from Schwartz’s modified Portrait Values Questionnaire (PVQ), which has been used in over 70 countries in the world in which validity has been consistently reflected in results across these countries (Schwartz (2007, p. 266) stresses that studies in over 65 countries support the theory and validity of the differentiation of values offered by the Schwartz Values Theory. The advantages of the PVQ include its ability to “present respondents with a more concrete and less cognitively complex task than the earlier value survey”, or SVS survey (Schwartz, 2007. p. 273). For Schwartz (2007, p. 273), this therefore “makes it suitable for use with all segments of the population”. Furthermore, Schwartz (2007, p. 274), argues that “respondents are asked to compare the portrait to themselves rather than themselves to the portrait”, where verbal items present a portrait of an individual with a certain values type. This is effective because asking respondents “to compare other to self directs attention only to the aspects of the other that are portrayed” and therefore “the similarity judgement is also likely to focus on these value-relevant aspects” Schwartz (2007, p. 274). The PVQ offers a superior method because if respondents are asked to compare “self to other” then attention would be focused on the self and, therefore, a larger number of self-characteristics might be recalled (Schwartz, 2007, p. 274). The PVQ is also suitable for different forms of administration, including self-completion questionnaires, and respondents “to the PVQ report no difficulty in making judgements and rarely ask questions or comment on the significance of the research”, treating the instrument “as a simple task” (Schwartz, 2007, p. 274).

The PVQ includes male and female versions and has no reversed items. Data gathered through both male and female PVQs were combined into a single analysis. For each portrait, respondents indicated an answer to the question: ‘How much is this person like you?’ which was measured using a 7-point Likert scale ranging from ‘Very much like me’ (1) to ‘Not at all

like me' (7). The PVQ scale measures ten basic motivational values, each of which contribute to one or more higher order values. These are summarised in Table 9, below.

Table 9: Portraits Values Questionnaire (PVQ**)**

	Self-Transcendence	Conservation	Self-Enhancement	Openness to Change
Universalism	3			
Benevolence	2			
Conformity		2		
Tradition		2		
Security		2		
Power			2	
Achievement			2	
Hedonism				2
Stimulation				2
Self-Direction				2
Total Items	5	6	4	6

3.8.5 The Organisational Climate Model (OCM)

Patterson, et al. (2005) describe the Organisational Climate Model (OCM); a multi-dimensional, global and aggregate approach to organisational climate, at the individual level of analysis, which takes four interlinking dimensions of organisational climate into account. The OCM offers a relatively comprehensive and flexible approach to the assessment of organisational climate and is both theoretically grounded and empirically validated (Patterson, et al., 2005).

The OCM consists of four models of climate, situated on a matrix from control orientation to flexibility orientation on the x-axis and internal focus to external focus on the y-axis. Patterson, et al. (2005) suggest that that dimensions (or models) of the OCM are customised according to context, or the purpose of the investigation. Thus, in an investigation pertaining to innovation amongst academic researchers, the contrast between the two extreme points of each dimension, the Internal Process Model (IPM) and the Open Systems Model (OSM), would seem most pertinent. In both models, innovation is positively associated with openness, flexibility and adaptability and negatively associated with closed, internal processes and models.

Both the IPM and the OSM have demonstrated acceptable internal consistencies, in previous studies (King et al., 2007; Patterson et al., 2005,). Innovative Climate is measured in Section E of the questionnaire (see Appendix 8.4.). Patterson, et al. (2005) assessed the internal consistencies of the constructs of the OSM, with the following Cronbach's Alpha scores: Flexibility and Innovation (.86), Outwards focus (.83), Reflexivity (.76). The constructs of the IPM, with Cronbach's Alpha score, are as follows (Patterson et al., 2005): Formalisation (.77), Tradition (.73). The standard form of the Innovative Climate Measure questionnaire is presented using a 5-point Likert Scale (Patterson et al., 2005) and comprises a total of 23 items.

3.8.6 Derivation of the Technological Propensity Scale

The technological propensity construct was measured quantitatively by using a set of scale items derived from the literature. Five dimensions of technological propensity are defined, including: i) tolerance for disruption; ii) technology use; iii) crowd propensity; iv) open orientation; and v) collaborative propensity. Table 10 depicts the construction of the scale items per technological propensity dimension for both the academic researchers and crowd-worker samples. Each of these dimensions was measured by way of a 5-point Likert Scale and respondents were asked to indicate the extent to which they agree or disagree with each statement. Each construct consists of four items, making for a total of 20 items in the measurement of technological propensity. Technological propensity was measured in Section F of the questionnaire (see Appendix 8.4.). The derivation and differences between the academic researcher sample and crowd-worker sample measurements of technological propensity are summarised in the table below.

Table 10: Derivation of the technological propensity scale (academic and crowd-worker samples)

	Academic Researcher Sample	**Crowd-Worker Sample**	**Reference**
	Tolerance for Disruption		
1.	I think it is important that journal publications exercise extreme caution in the publication of research that does not strictly adhere to broadly accepted research methodologies and paradigms [R].	I'm a firm believer in the term 'rules are rules' [R]	Campanario, 2009, Mahoney, 1977

	Academic Researcher Sample	Crowd-Worker Sample	Reference
2.	I do not often pursue research projects that are high risk [R]	I do not consider myself much of a risk-taker [R]	Rogers, 1995, Christensen, 1997; Christensen, 2013
3.	I am motivated by the fact that my research may hold the potential to introduce important change to the world	Technology is changing the world for the better	Callaghan, 2014a, Nonaka, 1994, Christensen, 1997
4.	The emergence of certain new technological advancements has made me look at my research from a new perspective	New technologies have made me look at the world from a new perspective	Drucker, 1994, Foster, 1986
Technology use			
1.	When I get sick, the first thing I do is look up my symptoms on the internet.	When I get sick, the first thing I do is look up my symptoms on the internet.	Torr-Brown, 2013, Afuah & Tucci, 2012
2.	I am always up to date with the latest technological advances like new software, applications, social networks and gadgets.	I am always up to date with the latest technological advances like new software, applications, social networks and gadgets.	Chesbrough, 2003a, Chesbrough, 2007
3.	These days it feels like there's a constant 'information overload' because of the Internet and how easily information is shared [R]	These days it feels like there's a constant 'information overload' because of the Internet and how easily information is shared [R]	Surowiecki, 2004, Rosenberg, 2016
4.	Wikipedia is a useless tool for academic research [R]	I wouldn't rely on Wikipedia if I want 100% accurate information [R]	Maehre, 2009, Kränbrig, et al., 2014)
Crowd Propensity			
1.	I would use online social media to collect research data (e.g. Twitter, Facebook, Instagram, etc.)	I would use online social media to try find a solution to a problem I have (e.g. Twitter, Facebook, Instagram, etc.)	Collier, et al., 2011,
2.	Solving serious research problems is best left to the professionals and academics [R]	Solving serious world problems is best left to the professionals [R]	Dewald, Thursby & Anderson, 1986, Hanson, 2000
3.	I would use crowd-funding (obtaining funds from a large undefined network of people to reach a monetary goal online, e.g. KickStarter) to obtain research funds	I would contribute money to a KickStarter project if I thought it was a good enough idea.	Palmer & Verhoever, 2015, Roberts, 2017

4	I am happy with my current method of obtaining research funding [R]	If I were to start a business of my own, I would use crowdfunding (e.g. KickStarter) to raise funding.	Roberts, 2017, Callaghan, 2014a
	Academic Researcher Sample	**Crowd-Worker Sample**	**Reference**
Open Orientation			
1.	I have used (or would use) Linux or other forms of open source software for my research	I think asking people's advice on social media is a great way to get a good answer.	Von Hippel, 1976, Lakhani & Panetta, 2007
2.	Problem solving doesn't require creative thinking – it requires hard facts and figures. [R]	Problem solving doesn't require creative thinking – it requires hard facts and figures. [R]	Lakhani & Wolf, 2003, West, 2003
3.	I generally stick to my own area of expertise – I'm not knowledgeable enough to research in other fields [R]	I am always interested to hear other people's opinions on current events.	Brabham, 2008, Bogers, et al., 2017
4	My research would benefit from perspectives from people from different fields of expertise – both academic and non-academic	I try get feedback on my ideas from family and friends	Callaghan, 2014a, Nonaka, 1994
Collaborative Propensity			
1.	I often collaborate with researchers from other disciplines on research projects.	If I have a problem, I'll usually try solving it myself before asking people for help [R].	Nonaka, 1994, Wang & Wang, 2012
2.	I only collaborate with researchers from my own research discipline [R]	I stick to what I know – I wouldn't comment on something I know nothing about [R]	King & Anderson, 2002, Anderson, et al., 2004
3.	I try to get feedback on my research from non-academics.	I like to work with different people from backgrounds that are different to mine	Chesbrough, 2003a, Howe, 2006
4.	I don't typically collaborate on my research projects; I prefer to work alone [R].	I don't enjoy teamwork; I prefer to work alone [R].	Welsh, 2013, Koboyashi, et al., 2007

3.9 INTERNAL VALIDITY

Cronbach's Alpha scores are calculated and reported as, indication of the scales' internal validity. The internal validity of i) the modified TIPI scale, ii) the PVQ and iii) and OCM are now reported. The Cronbach's Alpha scores provides for a measurement of discriminant validity (Field, 2012). Since the above-mentioned factors should be theoretically uncorrelated, reliability statistics are provided for each individual construct and for each sample (with AR

representing the academic researcher sample and CW representing the crowd-worker sample), as follows:

Table 11: Internal Validities

Personality (Modified TIPI)				
AR	**Construct**	**Items**	**Cronbach's Alpha**	**Reliable**
	Neuroticism	5	.767	Yes
	Conscientiousness	5	.684	Yes
	Extraversion	5	.765	Yes
	Agreeableness	5	.791	Yes
	Openness	5	.752	Yes
CW	Construct	**Items**	**Cronbach's Alpha**	**Reliable**
	Neuroticism	5	.758	Yes
	Conscientiousness	5	.683	Yes
	Extraversion	5	.814	Yes
	Agreeableness	5	.716	Yes
	Openness	5	.773	Yes
Motivational Values (PVQ)				
AR	**Construct**	**Items**	**Cronbach's Alpha**	**Reliable**
	Self-Transcendence	5	.676	Yes
	Self-Enhancement	4	.761	Yes
	Conservation	6	.731	Yes
	Openness to Change	6	.741	Yes
CW	**Construct**	**Items**	**Cronbach's Alpha**	**Reliable**
	Self-Transcendence	5	.878	Yes
	Self-Enhancement	4	.810	Yes
	Conservation	6	.823	Yes
	Openness to Change	6	.812	Yes
Work Climate Perceptions (The OCM)				
AR	**Construct**	**Items**	**Cronbach's Alpha**	**Reliable**
	Reflexivity	5	.748	Yes
	Outward Focus	5	.678	Yes
	Tradition	4	.760	Yes
	Innovation & Flexibility	6	.831	Yes
	Formalisation	5	.722	Yes
Organisational Climate Model (OCM) Components				
	Internal Process Model (IPM)	9	.776	Yes
	Open Systems Model (OSM)	16	.866	Yes

Gosling et al. (2003) suggest that the TIPI scale is usually less reliable than larger scales. However, the modified version of the TIPI used in this study exceeded expectations in both

academic researcher and crowd-worker samples since most items produced a Cronbach's Alpha score > 0.7. The Cronbach Alpha score of the PVQ and OCM seem to indicate stable internal validities across both sub-samples. Having reported the measures of internal consistencies, discussion pertaining to covariate selection and pilot studies follows.

3.10 COVARIATES

Questionnaires included measurements of basic biographical variables which may further influence the model of HR determinants that interact with productivity. These included gender, field of study, age, area of study (for the academic sample), industry and profession (for the crowd-worker sample), nationality and language.

3.11 PILOT STUDIES

A pilot study preceding the main observation was conducted by a verification test of the qualitative and quantitative instruments. For the qualitative study, the first two respondents were used as a test of the research instrument and interview process. This pilot test was conducted to determine the length and appropriateness of the instrument. Following the completion of the qualitative pilot test, it was discovered that no significant changes were needed.

For the quantitative study, two concurrent pilot tests were conducted, one for each sub-sample. For the both sub-samples, a pilot test was conducted using data from the first 50 completed questionnaires collected (an estimated 10% of the total sub-sample). This was done to assess the value of the research instrument and if the questions elicited the correct information for the primary research question as well as to ensure validity. This data was collected as per the method described above. For the academic sub-sample, questionnaires were distributed via email and for the crowd-worker sub-sample, questionnaires were distributed through MTurk.

All three pilot studies (both qualitative and quantitative) were conducted in the same manner as the full study; the same methodologies as described in this chapter as well as statistical analyses were used. The software used to analyse the data was IBM's SPSS 22.0 for Mac software. The results of the pilot studies indicated no significant problems with either the interview schedule or the questionnaire and no need to change either research instrument. Thus,

following the completion of the pilot study, it was evident that the research design, research instrument and characteristics of the sample were all sufficient and appropriate.

3.12 QUANTITATIVE DATA ANALYSIS: ANALYSES AND HYPOTHESIS TESTING

Following completion of the quantitative data collection, data was analysed. All statistical tests were conducted using IBM's SPSS 24.0 for Mac. All research questions and hypotheses were formally derived from the literature review section. The measurement of variables also forms the basis of the research hypothesis. In its null form, the research hypothesis is stated as: *technological propensity is significantly associated with productivity***.** A significance level of 5% was used to accept or reject the research hypothesis. In the following sections, each hypothesis tested in this research is introduced and discussed in relation to the variables tested, as well as the measures or scales of these variables, and the methods and statistical tests used. These sections are structured around the different hypotheses for the purposes of clarity and to provide a coherent structure which corresponds to the structure of the reporting of the results in Chapter 5.

Prior to hypothesis testing, a process of univariate analysis was undertaken to summarise the quantitative data collected and provide insight into the characteristics of the quantitative samples. For Ghauri and Gronhaug (2010) univariate analyses offer a means to summarise and organise data in an efficient and meaningful way. According to Zikmund (2010), the most common methods of summarising data are calculating the averages, the frequency distributions, and the percentage distributions of collected data. Data is organised into a frequency distribution as a way of organising it into a logical order (Howell, 2016). These distributions show how the variables are tabulated, contrasted to a frequency of occurrence (Howell, 2016). The determination of the central tendency describes the center of a frequency distribution of observations as measured by the mean, mode and median (Field, 2012). To ensure scientific rigour, the univariate data is represented with a frequency distribution; the normal distribution was checked using a histogram. Each biographical variable was assessed in this fashion. Biographical variables include: age, gender, country of birth, first language, years of experience, title, marital status, number of children supported in family, field of study (or industry and profession for crowd-workers), years of education, years of father's education and years of mother's education. Biographical variables were also subsequently used as covariate factors in the hierarchical multiple regressions during hypothesis testing. Descriptive

statistics pertaining to the individual measures of productivity are also included in the univariate analysis.

Exploratory Factor Analyses (EFAs) were conducted on each for each scale measure "to summarise the data in fewer dimensions" (Krommenhoek & Galpin, 2014, p. 433) or to uncover underlying latent variables (Field, 2012). Respective Cronbach's Alpha scores are also provided as a determination of scale reliability. Exploratory factor analyses (EFAs) were conducted to assess the convergent and discriminant validity (Campbell & Fiske, 1959) of scale-items from the questionnaires. Field (2012) suggests that a sample size over 300 is generally considered adequate for a factor analysis. The EFAs were conducted to identify correlations between observations that stem from their relationship to latent variables in the data, each of which takes the form of a linear model (Field, 2012). Prior to each EFA, a process of data screening was conducted, to detect any problematic inter-correlation between variables and issues relating to singularity (Field, 2012). EFAs were conducted on the modified TIPI scale (Gosling et al., 2003), the PVQ (Schwartz, 2012), the modified OCM (Patterson et al., 2005) and the technological propensity scale.

Following conclusion of the univariate analyses and EFAs, a process of multivariate analysis was undertaken to test this study's stated hypotheses. This process involved tests of bivariate correlations, hierarchical multiple regressions, as well as tests of mediation and moderation. Prior to each test of regression, dependent variables were transformed, using a natural log transformation to improve the robustness of the measure (Field, 2012).

3.12.1 Selection of covariates

For both samples, an assessment of theoretical precedent was used to determine which covariates should be included in tests of regression, mediation and moderation. This was done to reduce the number of covariates to be entered into the hierarchical multiple regressions and to adhere to the principles of parsimony (Gujarati & Porter, 2009). An EFA was conducted on all potential covariate factors to check for singularity and multicollinearity (Field, 2012). The process of multivariate analysis undertaken to test hypotheses is now discussed.

3.13 HYPOTHESIS TESTING: MULTIVARIATE ANALYSES

Research questions were derived from the literature. The overarching research question of this study is:

What is the relationship between technological propensity and productivity?

From this core research question, specific subordinate research questions and hypotheses were derived, and thereafter tested. These are discussed below, under the headings of hypotheses and represented as specification, as follows:

3.13.1 Hypothesis A1: Technological propensity is significantly associated with productivity

This hypothesis purports a positive relationship between technological propensity and productivity. First, a test of bivariate correlation was conducted to determine empirical associations (Field, 2012) between technological propensity and productivity. For the purpose of this study, non-parametric procedures were implemented as there was no underlying assumption of the sampling distribution being normally distributed (Field, 2012), The kurtosis identified in the univariate analysis was indicative of the suitability of using the Spearman's Correlation, which was performed on data that was converted into ranked scores (Field, 2012).

Multiple hierarchical regression was conducted to test the association between technological propensity and productivity, with the goal being the use of several independent (predictor) variables to predict a single outcome (Field, 2012). Predictor variables were entered in steps, in an order specified on theoretical grounds. This was done to control the effects of confounding variables and to ultimately build a better prediction model (Field, 2012). For both the academic researcher and crowd-worker samples, the regression equation is represented as follows:

$$Y\ (Productivity) = \alpha + Gender + Nationality + Language + Field/Profession + technological\ propensity + \varepsilon_i$$

In this specification, Y (productivity) represents the outcome variable and α represents the constant. The specification also contains the coefficients of each of the predictor variables. ε_i represents the difference between the predicted and the observed value of *Y* for the *i*th participant in the sample. In this specification, gender is a binary variable which classifies respondents as either men or women. Nationality classifies respondents by the country of their birth. Language classifies respondents by their home-spoken language. In the academic researcher sample, the variable Field is used to classify respondents according to their field of study. In the crowd-worker sample, the variable Profession is used to classify respondents into professions which are either Science, Technology, Engineering and Mathematics (STEM)-related or non-STEM related. The final predictor variable is technological propensity, which is a measure of an individual's technological propensity.

3.13.2 Hypothesis A2: Personality is significantly associated with technological propensity

First, a test of correlation was conducted to determine empirical associations between personality and technological propensity. Thereafter, this hypothesis was tested by a series of multiple hierarchical regressions, for each of the five components of the Big Five (or Five Factor Model) of personality, including i) openness to experience, ii) extraversion, iii) conscientiousness, iv) agreeableness and v) neuroticism (Costa & McCrae, 1992). For both samples, the regression equation is represented as follows:

$$Y\ (technological\ propensity) = \alpha + Gender + Nationality + Language + Field/Profession + Personality + \varepsilon_i$$

In this specification, the predictor variable personality is a measure of a respondent's personality, according to the Big Five Model of personality (Costa & McCrae, 1989).

3.13.3 Hypothesis A3: Motivational values are significantly associated with technological propensity

A test of bivariate correlation was conducted to determine empirical associations between higher-order motivational values and technological propensity. Several tests of multiple hierarchical regression were conducted to test this hypothesis, each relating to one of the higher-order motivational values defined by Schwartz (1992). These include i) self-transcendence, ii) self-enhancement, iii) conservation and iv) openness to change. For both samples, the regression equation is represented as follows:

$$Y\ (technological\ propensity) = \alpha + Gender + Nationality + Language + Field/Profession + motivational\ values + \varepsilon_i$$

In this specification, the predictor variable motivational values are a measure of a respondent's motivational values, according to the Schwartz (1992) model of motivational values.

3.13.4 Hypothesis A4: Work climate perception is significantly associated with technological propensity

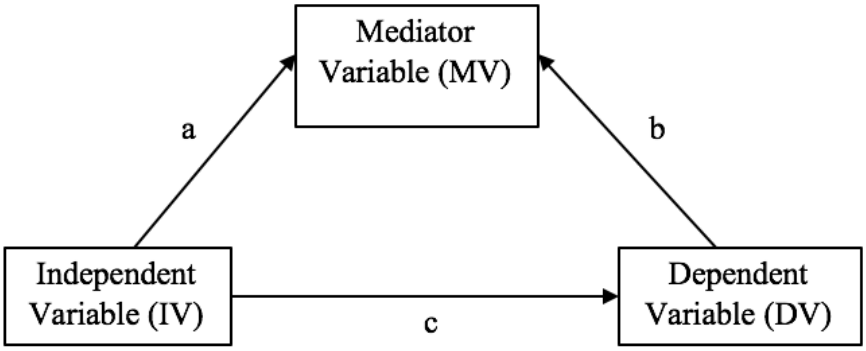
A test of bivariate correlation was conducted to determine empirical associations between work climate perceptions and technological propensity. This hypothesis was tested by conducting two tests of multiple hierarchical regression. Both Internal Process Model (IPM) perceptions and Open Systems Model (OSM) perceptions were tested for association with technological productivity. As previously mentioned, this hypothesis was tested for the academic research sample only. The regression equation is represented as follows:

$$Y\ (technological\ propensity) = \alpha + Gender + Nationality + Language + Field/Profession + climate + \varepsilon_i$$

In this specification, the predictor variable climate is a measure of a respondent's work climate perceptions, according to the Organisational Climate Model (Patterson, et al., 2005).

3.13.5 Hypothesis A5: Personality mediates the relationship between technological propensity and productivity

Five tests of mediation were conducted to determine the interactive effect of each of the components of the Big Five Model of personality on the relationship between technological propensity and productivity. All tests of mediation were conducted using Hayes' (2012) PROCESS method for SPSS. Mediation is the term used to refer to the variable that "serves to clarify the nature of the relationship between the independent and dependent variables" (MacKinnon, 2008. p. 447). A mediator variable is thus one that influences the relationship between a dependent and independent variable, which in turn influences the mediating variable itself. All tests of mediation followed Baron and Kenny's (1986) mediation model, as per Figure 13, below.



1. Total effect: $c = ab + c^2$
2. Direct effect: $c^2 = c - ab$
3. Indirect effect: $c - c^2 = ab$

Figure 13: Mediation Model (Adapted from Baron & Kenny, 1986, p. 1176)

3.13.6 Hypothesis A6: Motivational values mediate the relationship between technological propensity and productivity.

Each of the four higher order motivational values were tested for their mediating effect on the relationship between technological propensity and productivity. Baron and Kenny's (1986) 3-step process for mediation was once again employed, as per Figure 11.

3.13.7 Hypothesis A7: Climate Perceptions mediate the relationship between technological propensity and productivity

Both IPM and OSM climate perceptions were tested for their mediating effect on the relationship between technological propensity and productivity. This hypothesis was tested for the academic researcher sample only.

3.13.8 Hypothesis A8: Human capital investments (HCI) mediate the relationship between technological propensity and productivity

For academic researchers HCI was measured by number of years of experience as an academic researcher. For crowd-workers, HCI was measured by level of education. For both samples, HCI was tested for its mediating effect on the relationship between technological propensity and productivity.

3.13.9 Hypothesis B1: Human capital investments (HCI) are significantly associated with productivity

A test of bivariate correlation was conducted to determine empirical associations between HCI and technological propensity. This hypothesis was tested by conducting a test of hierarchical multiple regression where HCI was tested for association with productivity. The regression equation for both samples represented as follows:

$$Y\ (Productivity) = \alpha + Gender + Nationality + Language + Field/Profession + HCI + \varepsilon_i$$

In this specification, the variable HCI are a measure of a respondent's human capital investments. In the academic researcher sample, HCI are measured by an aggregate total of years of experience as an academic researcher. In the crowd-worker sample, HCI are measured by level of education received.

3.13.10 Hypothesis B2: Personality mediates the relationship between human capital investments (HCI) and productivity

Each of the five personality types of the Big Five Model were tested for their mediating effect on the relationship between HCI and productivity.

3.13.11 Hypothesis B3: Motivational values mediate the relationship between human capital investments (HCI) and productivity

Each of the four higher order motivational values were tested for their mediating effect on the relationship between HCI and productivity.

3.13.12 Hypothesis B4: Climate perceptions mediate the relationship between human capital investments (HCI) and productivity

Both the IPM and OSM climate perceptions were tested for their mediating effect on the relationship between HCI and productivity.

3.13.13 Hypothesis C1: Gender significantly moderates the relationship between technological propensity and productivity

Tests of moderation were also conducted using Hayes' (2012) PROCESS method for SPSS. The term 'moderation' is used to describe the effect of a variable on the relationship between two other variables (MacKinnon, 2008). For Field (2012, p. 407), "moderation occurs when the relationship between the variables changes as a function of a third variable". This third variable is characterised as an interaction that is categorical (MacKinnon, 2008). Several tests of moderation were conducted. Firstly, the moderating effect of gender on the relationship between technological propensity and productivity assessed differences across male and female respondents. This test was conducted following the method prescribed by Baron and Kenny (1986), depicted in Figure 14 below.

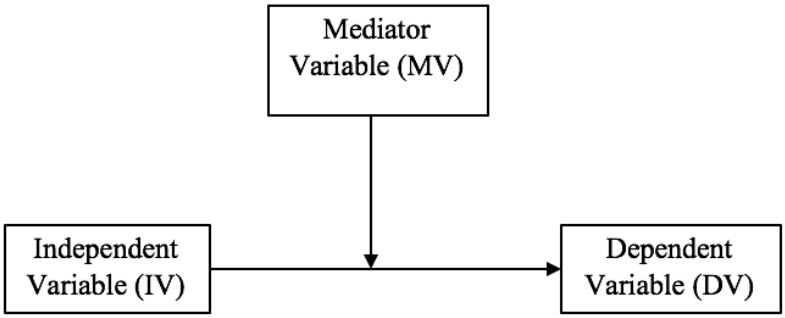


Figure 14: Mediation model (adapted from Baron & Kenny, 1966, p. 1174)

3.13.14 Hypothesis C2: Area of expertise significantly moderates the relationship between technological propensity and productivity

Secondly, 'field of study' for academic researchers and 'profession' for crowd-workers was tested for moderation on the relationship between technological propensity and productivity. For the academic researcher sample, field of study comprises four areas of expertise, including i) Commerce, Law and Management (CLM), ii) humanities, iii) sciences, and iv) health sciences. For crowd-workers, profession comprises two categories, including i) Science, Technology, Engineering and Mathematics (STEM) and ii) non-STEM.

3.13.15 Hypothesis C3: Gender significantly moderates the relationship between human capital investments (HCI) and productivity

A third test of moderation was conducted to assess differences across the sample's male and female respondents in relation to the association between productivity and HCI.

3.13.16 Hypothesis C4: Area of expertise significantly moderates the relationship between human capital investments (HCI) and productivity

A final test of moderation was conducted to assess differences in fields of study (for academic researchers) and profession (for crowd-workers), and its impact on the relationship between productivity and HCI.

3.14 BOOTSTRAPPING

'Bootstrapping' is a process used "to churn (or regurgitate) a given sample over and over again and then obtain the sampling distributions of the parameters of interest (Guajarati & Porter, 2009, p. 510). The process of bootstrapping is used when the normality assumption cannot be maintained on the basis of various normality tests, as is the case for the samples in question in this research. Thus, for both samples all regression, mediation and moderation analyses were bootstrapped at either 1 000 or 5 000 iterations, depending on SPSS capability (the SPSS capability restricts regression analysis to a maximum of 1 000 bootstrapped iterations while tests of moderation and mediation are restricted to a maximum of 5 000 bootstrap iterations). Results of the hypothesis testing described above are provided in detail in Chapter 5. In the next two sections, a discussion of ethical considerations and limitations associated with this research follows.

3.15 ETHICAL CONSIDERATIONS

The research proposal was submitted to Wits University's Ethics Committee for approval and approved unconditionally. This research follows the ethical principles of social science research. Sensitivity to the protection of anonymity was maintained in both the quantitative and qualitative analyses. Only questions were that were relevant to the research questions and informed consent (Anastasi, 1990) were posed. Both qualitative and quantitative respondents were required to sign consent forms before participating in the research. In the case of the qualitative respondents, no biographical details were collected, to protect anonymity. Quantitatively, all data was analysed in aggregate so that no individual could be identified. In all instances, potential respondents were made aware that participation in the research was entirely voluntary and that they may withdraw from the research at any time with no risk or consequence. The ethical principle of anonymity necessitated the use of self-reports of research productivity. While this may have introduced common method bias, this was considered unavoidable if the ethical imperative of anonymity was to be upheld unconditionally. Participants consent forms, information sheets in the form of cover letters, and audio recording consent forms were used. These forms are included in Appendix 8.4. However, in line with the requirements of anonymity signed forms are not included in the final document. Limitations relating to the research are now considered.

3.16 LIMITATIONS

Certain limitations relating to the sampling process may be an impediment. Many potential respondents refused or declined to participate. This may have skewed the representivity of the sample. Individuals that are more interested in the research may be more highly represented and those who were not willing to participate (or were uninterested in the research) might be highly under-represented. It is also acknowledged that some data collected from respondents may have been exaggerated or false. Causality limitations were expected to form one of the limitations of this research. The quantitative testing process demonstrated significant statistical relationships, but the causes of phenomena could not be proved by such a process of testing. The nature of this research was primarily exploratory. The research design did however, attempt to address certain challenges associated with academic research and sought to test relationships around research productivity (more specifically, breakthrough research productivity). This was done by employing a qualitative process as well as a quantitative process, to develop and to test theory. It is argued that this approach allowed certain theory to emerge which was not present in the literature. The quantitative testing was found to support the theory developed from the qualitative analysis.

No attempt to explain the exact causes of certain phenomena was made. In the context of social research, the impossibility of measuring every single variable that may influence research productivity is acknowledged. An attempt to counteract the influence of common method bias was made by administering the Harmon test to the data, once acquired (Podsakoff, P. M., MacKenzie, Lee & Podsakoff, N. P. 2003). It is also noted that the cross-sectional nature of this study may pose a limitation (Shipman, 2014). An attempt was made to mitigate this limitation to some extent by using theory to specify relationships to test. In this way, theory was tested; although, further longitudinal research in this context is recommended. It is also acknowledged that the tested measures of this research represented only a minute fraction of the relationships that act on the individual. The multi- determined nature of social science factors is also acknowledged as a limitation to this and other research within the social sciences.

In this research, certain human resources management variables were investigated, yet a range of other factors which may be physiological, psychological and biological were not specifically investigated as they are regarded beyond the scope of this research as it is limited to its level of analysis. In this sense, an attempt is made to keep the level of analysis appropriate to the

answering of the research questions. Also acknowledged is that there is a limitation inherent in not including a more exhaustive set of factors due to practical constraints in the analysis.

Attempts were made to mitigate the influence of method bias. The Harmon test for method bias (Podsakoff et al., 2003) was applied to the data. This method indicated that no dominance of common method bias was present. Also, the use of both qualitative and quantitative components in the research support a holistic analysis in that the quantitative results were analysed in relation to the qualitative analysis ensured that findings and recommendations were supported by both before they were taken as supported by the findings of the study.

The limitations discussed above were recognised and a careful process of data collection and analysis was undertaken to lessen the impact of these limitations. This chapter is now concluded, as follows.

3.17 CHAPTER CONCLUSION

In this section, the methodology that applies to this research was introduced and discussed. Both the qualitative and quantitative research components were introduced, and the research was located in relation to suitable paradigms, both ontologically and epistemologically. The mixed methodology procedure that applies in this research was introduced and discussed, as were the issues relating to the verification of the qualitative research process. The process of qualitative analysis was described, including a discussion on coding, analysis, and qualitative sampling. The quantitative analysis was described thereafter, including a discussion regarding the research design, scope of the study and the study populations and samples. A description of the sampling process, sample size calculation, sampling protocol and interview processes was also provided, as was the reliability and validity of the study. This was followed by a description of the processes employed to formulate the scales of measurement with reference to the pertinent literature. Thereafter, the hypotheses were introduced in relation to the statistical methods and measures used to test them.

Having introduced and discussed the qualitative and quantitative methodology of this research, the next two chapters (Chapters 4 and 5) are now reported. This follows precedent in this field of study, namely, to justify the holistic perspective required of this research after a comprehensive literature review (Chapter 2) and introduction of the different research

methodologies (Chapter 3). The next chapter (Chapter 4) reports and discusses the qualitative results of the research process by extending the literature review and methodology to the results of the data analysis. The quantitative results will be reported in Chapter 5.

CHAPTER 4
QUALITATIVE ANALYSIS (STUDY 1)

4.1 INTRODUCTION

In the previous chapter, the methods used in this study were reviewed and justified. The results of the inductive qualitative analysis are now reported. This analysis seeks to develop theory that relates the phenomena under study and to develop a model of these relationships that is grounded in the context of extremely productive researchers. It also seeks to develop theory relating to Breakthrough Research Productivity (BRP). Qualitative data was gathered from 30 award-winning scientists, researchers and academics from around the world. Amongst these are 3 Nobel Prize winners, 3 Lasker Award winners and 1 Fields Medal winner, among others.

The primary purpose of the qualitative analysis therefore is to investigate the determinants of BRP. The reporting of the results in this chapter follows the structure of headings that represent certain propositions derived from analysis. Each proposition relates to a different proposed determinant of BRP. The most notable finding of the qualitative analysis is that the determinants of BRP can be split into two categories: i) internal drivers of BRP and ii) external drivers of BRP. It is argued that these two categories impact BRP in different ways. Internal drivers, including personality, motivation, innate ability and technological propensity represent drivers or influences that are inherent to the individual and may therefore differ from person to person. External drivers include human capital investments (HCI), work climate and resource availability, which are distal to the individual, and that may impact performance. These may therefore differ serendipitously, based on a range of differences including geographical location, upbringing, nationality, gender, age, social environment and experience. Based on these findings, two major propositions are derived from the qualitative analysis. Proposition A relates to the relationship between internal drivers and BRP. Proposition B relates to the relationship between external drivers and BRP. Each of these propositions is then further delineated to sub-propositions, which relate to the relationships between the specific internal or external drivers and BRP.

It is stressed that only the results of the qualitative analysis are reported in this chapter. These results are discussed in further detail, and related to literature, in Chapter 6. In this chapter, the findings of the qualitative analysis are detailed, with reference to tables that summarise overarching and sub-themes found to relate to BRP and the propositions that are derived from them. The process of qualitative coding and analysis is now described.

4.2 QUALITATIVE CODING AND ANALYSIS

The qualitative data was processed, using a process of inductive analysis. Interview transcripts were transcribed. Thereafter, a coding process commenced and was continued until a point of theoretical saturation was reached (Miles & Huberman, 1994; Guest, Bunce & Johnson, 2006). The final codes related to the themes were identified as components of the overarching theoretical constructs. The analysis reported in this chapter follows a form of inductive qualitative analysis, as prescribed by Thomas (2006) and Miles, Huberman and Saldana (2014). These principles are applied by using thematic content analysis. The analysis reveals relationships that are both within and beyond the scope of this study. Only relationships and themes relevant to the study are discussed. In the context of this research, winners of major scientific awards are considered to have produced a high level of breakthrough research productivity. Nobel Prizes, for example, are awarded "in recognition of academic, cultural, or scientific advances" (Nobel Prize, 2017; p.1). In this sense, the receipt of a major scientific award is tantamount to recognition of producing a radical breakthrough. By definition, a radical innovation, is a disruptive breakthrough that supplants existing models, and replaces them with something new (Smith, 2010). Therefore, recipients of major scientific awards represent individuals who have produced a radical scientific or academic innovation. The objective of this analysis is to uncover the determinants of radically innovative scientific research, referred to as BRP. The dominant theme that presented itself in the analysis was that of a difference between internal and external drivers of BRP. The general trends of the qualitative sample are now discussed.

4.3 GENERAL TRENDS

The mean age of respondents was 73.5 years. Male respondents accounted for 86.7% of the sample (26 respondents). Female respondents accounted for 13.3% of the sample (4 respondents). 63.3% of respondents were American (from the USA). 16.7% of respondents were from Europe and the UK. The remainder of the sample were from countries outside of the USA, Europe and the UK. A summary of the qualitative sample is provided in Table 12, below.

Table 12: Summary of qualitative respondents

	Notable Award(s)	Field of Study	Gender	Age
1	A1-Rated Researcher, South African NRF	Geochemistry	Male	61
2	International Grand Prix Award for Medicine and Water	Nutritional Science	Male	68
3	Nobel Prize in Physiology or Medicine	Biochemistry & Molecular Biology	Male	74
4	The Turing Award	Computer Science	Male	76
5	Nobel Prize in Physics, Wolf Prize in Physics	Physics	Male	79
6	Einstein Prize, Shaw Prize	Physics	Male	85
7	Lasker Award for Basic Medical Research	Cell Biology	Male	71
8	The Turing Award	Computer Science	Female	78
9	The Wolf Prize in Agriculture	Plant biology	Male	73
10	The Wolf Prize in Agriculture	Microbiology	Male	78
11	Fields Medal, Wolf Prize, National Medal of Science	Mathematics	Male	68
12	L'Oréal UNESCO Award for Women in Science	Molecular biology	Female	59
13	Nobel Prize in Physics, Wolf Prize	Theoretical Physics	Male	71
14	National Academy of Science	Particle Physics	Male	61
15	Breakthrough Prize in Science, Albert Einstein Award	Molecular biology, oncology	Male	75
16	Lasker Award for Basic Medical Research, Wolf Prize in Medicine, Breakthrough Prize in Life Sciences	Biology	Male	64
17	Breakthrough Prize in Fundamental Physics	Particle Physics	Male	69
18	Kyoto Prize, Albert Einstein Award,	Evolutionary Biology	Male	78
19	National Medal of Science	Neuroscience	Male	81
20	Shaw Prize	Astrophysics	Male	73
21	Shaw Prize	Theoretical Astrophysics	Male	56

	Notable Award(s)	Field of Study	Gender	Age
22	National Medal of Science, MacArthur Prize Fellowship	Political Science	Male	74
23	National Medal of Technology	Electrical Engineering	Male	83
24	National Medal of Science	Archaeology	Male	85
25	National Medal of Science	Chemistry and biochemistry	Female	76
26	National Medal of Technology and Innovation	Cancer biology	Male	77
27	Lasker Award for Clinical Medical Research	Ophthalmology, epidemiology	Male	75
28	National Medal of Science	Earth and environmental sciences	Male	86
29	MacArthur Prize Fellowship, National Medal of Science	Statistics	Male	79
30	L'Oreal-UNSECO Award for Women in Science	Hydrodynamics	Female	58

4.4. DERIVATION OF PROPOSITIONS

The reporting of the results in this section follows the findings of the qualitative analysis. This chapter does not include a discussion of results in relation to literature. The discussion of qualitative results is contained in Chapter 6. First, Proposition A, which relates to the relationship between internal drivers and BRP is reviewed. Second, Proposition B, which relates to the relationship between external drivers and BRP is considered. For the purpose of this study, the term 'internal drivers' is used to refer to internal differentiators such as personality, motivation, innate ability and technological propensity. The term 'external drivers' is used to refer to external influences such human capital investments, work climate and resource availability. A discussion follows, with references to the overarching themes and sub-themes found to relate to BRP. Proposition A, relating to internal drivers is examined first, as follows.

4.4.1 Proposition A: Internal drivers such as personalities, motivations, innate abilities and technological Propensity aligned to breakthrough research behaviours are positively related to BRP

Internal drivers are used to refer to internal, individual-level differentiators, including personality, motivation, innate ability and technological propensity. Qualitative analysis revealed the importance of these drivers in the attainment of BRP. For many respondents, the internal desire or urge to discover the truth and to acquire new knowledge may be the primary driver of BRP. The relationship between each of these drivers and BRP forms the foundation for the derivation of sub-propositions that fall under Proposition A. Each sub-proposition is comprised of a number of sub-themes. Proposition A1 is discussed first, as follows.

4.4.1.1 Proposition A1: Humble, enthusiastic, open, conscientious and extraverted personalities are positive drivers of BRP

Personality was found to be an important precursor to innovative research behaviour. Sub-themes related to personality include i) humility, ii) enthusiasm, iii) openness, iv) conscientiousness and v) extraversion. The following sub-themes, related to personality, are provided in Table 13 below.

Table 13: Personality (sub-themes)

Theme	Theme Title	Key concepts	Respondents
1	**Humility**	honesty, humble, luck, insecurity	R02, R04, R18, R19, R24, R28
2	**Enthusiasm**	passionate, energetic, excitement	R03, R10, R11, R14, R16, R24, R30
3	**Openness**	creativity, curiosity, inventiveness, imagination, inquisitive	R8, R10, R11, R16, R19, R21, R23, R25, R29
4	**Conscientiousness**	persistence, perseverance, independence	R5, R7, R10, R11, R12, R22
5	**Extraversion**	collaboration, communication, interactivity, sharing	R5, R9, R23, R25

4.4.1.1.1 Sub-Theme A1.1: Humility

Many respondents demonstrated high levels of humility, despite their status as some of the most successful scientists in the world. Some attributed their success to "*dumb luck*" (R28) and "*chance*" (R19) and downplayed the importance of their ground-breaking achievements.

> "*I don't understand quite why it's so ground-breaking, but people consider it so*" (R04).

> "*I don't think my research has had any breakthroughs*" (R18).

> "*That idea was something somebody else would have thought about in a couple of years – I just happened to be there first*" (R28).

Notable references were made to "*absence of hubris, humility*" (R02), and the ability to remain "*completely honest … being willing to consider that you may be wrong*" (R04) as important contributing factors to the attainment of BRP. One respondent suggested that it is important to acknowledge that there will always be others with greater skill and more expertise than oneself, and that being able to work with such individuals can be a powerful advantage. However, some respondents were careful to note that those researchers who lack humility or modesty may suffer the opposite effect.

"*I was able to put together teams … that were more expert than me… a colleague that … wanted to run everything on his own and he picked up a lot of flunkies. And I was successful, and he was not because I was trying to find people who were better than me, he was afraid of picking people who were better than himself. I guess he was insecure*" (R24).

Based on these findings, it is proposed that humility is a positive driver of BRP. Individuals that display humble characteristics and are not immodest regarding their achievements may be more likely to view their own and others' research in a more realistic light and may therefore be more able to identify and take advantage of opportunities for breakthrough research productivity.

4.4.1.1.2 Sub-Theme A1.2: Enthusiasm

Enthusiasm, or passion for scientific research and the thirst for knowledge was another powerful theme that emerged, as a sub-theme of personality.

"*People who are really enthusiastic about science … for me that is the single most important criteria*" (R03).

This sub-theme linked closely to that of sub-theme A1.3 (openness), in that curiosity was considered a driving force of enthusiasm and energy:

"*If he's not energetic or not full of curiosity, he won't make the discoveries because he's not interested to look for something new*" (R11).

Most respondents maintained that they have a strong innate passion for scientific research, as evidenced by their achievements and through the actions taken to attain their breakthroughs.

"*I fought very hard and loudly to make sure things happened*" (R14).

Energy and excitement seem to function as important drivers of goal-achievement. Respondents were also careful to note that enthusiasm and passion should not be too narrowly focused.

"*If somebody's focused on a particular narrow goal … they're not open to fresh ideas, they're not open to surprises*" (R16).

Conversely, being able to "*focus [one's] energy in the right direction*" and "*not worry about things that are not so important*" (R14) was suggested as the best way to apply enthusiasm. This quote shows the dichotomous nature of enthusiasm, which if left unchecked may stifle innovation rather than stimulating it. Based on these findings, it is proposed that enthusiasm is a positive driver of BRP. Individuals that are passionate, energetic and approach their research with a sense of excitement may be more likely to identify opportunities to innovate and therefore, produce breakthrough research outputs.

4.4.1.1.3 Sub-Theme A1.3: Openness

Openness emerged as perhaps the strongest and broadest sub-theme of personality. Openness was found to consist of several interlinking components. Most notable of these is curiosity and creativity. Openness linked closely to extraversion (sub-theme A1.5), with common references to "*scientific gregariousness*" (R16, R29) or "*openness to fresh ideas*" (R16). One of the most frequently cited sub-themes of openness was curiosity. Curiosity was often cited as perhaps the most important contributor to innovation. This can be seen in the following responses that emphasised scientific curiosity:

"*Curiosity drives everything*" (R11).

"*[The ability to]* "*ask questions*" (R11), "*make connections to new areas*" (R21), and "*to be intellectually nimble*" (R16).

Curiosity was closely associated with independent thought, a theme also prevalent in sub-theme A1.4 (conscientiousness). This theme related to a willingness or propensity of scientific researchers to consider all potentialities, including those which may be at odds with conventional wisdom (or, dogma). The term 'thinking outside the box' was used frequently to describe this phenomenon. However, it was also noted that 'outside-the-box-thinking' must be managed carefully. A foundation of knowledge (i.e. education) was cited as an important precursor to scientific creativity.

"*[one must] know what's going on in the box, before ... [one] goes outside the box*" (R10).

Creativity was often mentioned in conjunction with curiosity. Creativity was seen as a conduit through which to channel curiosity.

"*It's really about creativity more than anything I think"* (R25).

Respondents referred to "*imagination*" (R19) as a requirement for productive creativity and its outcomes such as "*discovery and the patenting of new ideas, creating new products*" (R09). However, creativity was rarely cited as a stand-alone phenomenon. Instead, it was noted that creativity should be combined with "*training, skill*" (R23) and "*breadth and depth of understanding*" (R08). This suggests that creativity is viewed as a periphery to curiosity and the broader sub-theme of openness. It is therefore perhaps also associated with HCI.

Independence was also found to relate to openness. This was described as a "*contrarian attitude*" (R29), or a personality that is critical of conventional wisdom. Based on these findings, it is proposed that openness is a positive driver of BRP. Individuals that make use of their creativity, are inherently curious inventive and that have active, dynamic imaginations may be more likely to be deeply engaged with their research. As a result, opportunities to innovate may become more commonplace and may be more likely to be exploited.

4.4.1.1.4 Sub-Theme A1.4: Conscientiousness

Conscientiousness relates to independence (or, independent thought), perseverance and persistence. Independence was also described as a "*bloody-mindedness*". Independence manifests itself through a willingness to "*stick your neck out*" (R05), being *"adventurous and fearless*" (R12) or holding beliefs "*with no hesitation*" (R10) in finding *"something new in a direction that's different*" (R07).

Respondents also noted the delicate balance between self-confidence and arrogance. This differentiation must be carefully distinguished, as overcompensation on either side of that balance may be problematic. The general trend seemed to indicate support for the notion that

the pursuit of one's *"own intuitions in the face of others saying 'they don't get it'"* (R22) may perhaps outweigh the importance of being "*egocentric*" (R05). It was also often noted that this type of aggressive drive is an important complement to conscientiousness, if managed well. As previously discussed, the sub-theme of conscientiousness is closely linked to that of openness.

> *"[T]here have been many people who may have creativity*, *who may be curious, but they cannot persist to look at the problem and they gave up"* (R11).

> "*Obviously, you have to certain amount of perseverance because sometimes it doesn't come that easy*" (R05).

> "*If you cannot focus, if you cannot persist to work on hard … you won't be able to create great work. All the great work … has had some hard work behind it* (R11).

In this way, conscientiousness may act as a driver of openness (including creativity and curiosity), providing both focus and depth to push from ideation towards innovation. Based on these findings, it is proposed that conscientiousness is a positive driver of BRP. Individuals that are diligent, persistent (even in failure) and who display an independent spirit may be more likely to produce radically innovative outcomes, owing to their perseverance and high level of attention to detail.

4.4.1.1.5 Sub-Theme A1.5: Extraversion

Extraversion emerged as perhaps the weakest of personality traits required to stimulate innovation. One respondent noted that collaboration was a non-essential component of innovation.

> "*I haven't looked to collaborate deliberately and sought out fresh ideas from other people. I've tried to come up with my own*" (R05).

This suggests a link to independent thought (as a component of conscientiousness). This particular quote, however, may be an exceptional one. The overarching sentiment amongst respondents was that extraversion, collaboration, communication and cooperation do indeed

stimulate innovation. Some respondents linked the humanistic or worldview motivation to the ability to communicate with others.

> *"[T]hose on the outside of the community, so that we make the academic community to be able to speak to the non-scientists or the semi-informed scientists, to be able to able to share information*" (R09).

Most respondents agreed that "*interactive skills*" (R25) and the "*ability to collaborate with others*" (R23) were important contributors to attaining research breakthroughs. Based on these findings, it is proposed that extraversion is a positive driver of BRP. Individuals that are more willing to collaborate with their peers, are adept communicators and who seek interactivity and sharing may be more likely to be exposed to a greater volume of external knowledge and ideas. As a result, such individuals may be more likely to overcome the problem of knowledge aggregation and may ultimately therefore be more likely to produce radically innovative research outputs. Proposition A2, relating to the relationship between motivation and BRP is now discussed, as follows.

4.4.1.2 Proposition A2: Motivations that are intrinsic such as resilience, the pursuit of satisfaction and altruism (world view) are positive drivers of BRP

The term motivation is used to refer to the "mainspring of behaviour" (Hancock, 1992, p. 7). Sub-themes related to motivation, that emerged from qualitative analysis, are shown in Table 14 below.

Table 14: Motivation (sub-themes)

Number	Theme Title	Key concepts	Respondents
1	**Pure Intrinsic motivation**	personal, interest, passion, independence, curiosity, ambition, satisfaction, knowledge, answers	R1, R2, R3, R12, R16, R17 R19
2	**Satisfaction**	Fun, enjoyment, creativity, adventure	R6, R9, R12, R30
3	**Resilience**	Belief, pride, optimism, individualism	R1, R5, R7, R12, R23, R30
4	**World View**	humanistic, help, difference, contribute	R9, R19, R22, R23, R30
5	**Extrinsic**	money, power, respect	R17, R22, R23, R29

4.4.1.2.1 Sub-Theme A2.1: Pure Intrinsic Motivation

Pure intrinsic motivation emerged as one of the strongest themes relating to motivation. Intrinsic motivation refers to motivation that stems from an internal desire to conduct academic research and is considered antithetical to extrinsic motivation.

> "*I don't do research for fame or for money … it's what we're interested in" (R01)*.

Many respondents eschewed the pursuit of research in return for extrinsic rewards, preferring "*some kind of an internal desire*" (R19) and "*truth; not in it for money, just in it to find the truth*" (R02). Intrinsic motivation also linked to creativity, which was similarly described as an internal process. It was noted that creativity can be fostered, nurtured and developed over time, but could not be stimulated by external forces. Intrinsic motivation was also shown to be associated with independence, as shown in the following responses:

> *"A researcher should be strongly motivated to do his or her research*" (R13).

> "*There isn't anybody telling you what to do. All that happens is you get measured based on your results. So, if you happen to be good at finding new problems that are important and you get results, you know that's good [and] you'll succeed. If you aren't making progress, you'll fail*" (R09).

The term 'pure' is used to describe motivation that is related to fulfilling a need. For many respondents in the sample, the pursuit of knowledge is tantamount to a fundamental desire for truth. For this reason, this sub-theme links to sub-theme A2.2 (satisfaction), in that *"[finding] the truth*" (R02) satisfies a fundamental need and is therefore a powerful driving force behind BRP.

> "*You have to be constantly burning in your head to want to answer a key question*" (R12).

Some respondents referred to the excitement (rather than disappointment) in attaining an unexpected result and its subsequent satisfaction after conducting research:

"*I really want to hear about your failures because failure just means either you didn't plan the experiment properly or more excitingly, it means that something we thought we knew about nature isn't true"* (R03).

"*Because they were mystified by what this gene was doing, they were highly motivated to get the answer. They were operating on a strong faith that whatever the answer was, it was going to be really interesting and worth all their effort"* (R16).

"*You need people who are motivated by the call, by the over-arching goal to make some discoveries, … they're always driven by the motivation to do something unique and exceptional and fundamental"* (R17).

This appetite, or desire for knowledge, may indeed be the anchor of motivation in the attainment of BRP. Based on these findings, it is proposed that pure intrinsic motivation is a positive driver of BRP. Individuals that are intrinsically motivated or motivated by factors that are inherent to the individual, such as curiosity, independence, the seeking of satisfaction, knowledge or answers to questions may be more likely to produce innovative research outputs than their peers.

4.4.1.2.2 Sub-Theme A2.2: Satisfaction

Satisfaction may be considered a sub-component of sub-theme A2.1 (pure intrinsic motivation). However, satisfaction may not be 'pure' intrinsic motivation. This is because satisfaction relates to the outcomes of the pursuit of knowledge, rather than the pursuit of knowledge itself. Key terms such as 'fun' and 'love' were used to describe these satisfactory outcomes of acts spurned by purely intrinsic desires.

"*I wanted to know more and more … very satisfying to someone like me*" (R09).

"*You have to have fun. That's really the motivation"* (R06).

"*It's great, great fun*" (R09).

The difference between 'fun' and 'love', however, must be noted.

"[Research is a] vocation, it's a lifestyle. This is not something that you walk into the office and start doing at 9 in the morning and leave at 5 in the evening. Top researchers are consumed by what they do" (R12).

This quote clearly shows the relationship between motivation and personality. More specifically, this quote shows the importance of enthusiasm and passion in the pursuit of innovation. It also shows the importance of work-derived satisfaction. Based on these findings, it is proposed that satisfaction is a positive driver of BRP. Individuals that seek to derive pleasure from their research in the form of fun, enjoyment or a sense of adventure may be more deeply engaged in their work and may therefore be more likely to identify and take advantage of opportunities to produce radically innovative research outputs.

4.4.1.2.3 Sub-Theme A2.3: Resilience

Resilience is defined as willpower, determination and "*bloody-mindedness*" (R05), or "*stamina*" (R30) and the ability to "*take failure*" (R12).

"*Resilience … is a key characteristic*" (R12).

The attaining innovation may require high levels of "*bravery*" and a willingness "*to have that delayed gratification*" (R07). This sub-theme was also shown to be related to the difference between incremental and radical innovation. Both types of innovation were considered important. Resilience may apply to the pursuit of either type of innovation. In the context of this research (which is focused on radical, or breakthrough innovation), respondents generally tended to agree that a sense of resilient "*optimism"* (R12) and the acknowledgement of delayed gratification would be important to "*overcoming barriers*" (R07) of obtaining radical breakthroughs.

Perseverance and persistence are both key characteristics of resilience. These were also referred to as 'belief' (R01, R23), or a certain level of faith required to motivate oneself against seemingly insurmountable odds. This belief was also referred to a "*responsibility for your own fate*" (R08). Based on these findings, it is proposed that resilience is a positive driver of BRP.

Individuals who are optimistic, take pride in their work and maintain a tenacious belief in their ability to produce breakthrough research outputs may be more likely to do so.

4.4.1.2.4 Sub-Theme A2.4: Worldview

Worldview refers to an altruistic, or humanistic perspective that functions as a motivational force.

> "*[W]anting to contribute something meaningful to the world, wanting to make a difference, wanting to help*" (R22).

The worldview motivation emerged most strongly from respondents in medical and health research fields, described as a strong willingness to help others. This sub-theme was also present in respondents that studied global warming and plant and crop biology. "*Passionate belief ... will have a major impact for the world*" (R23). Altruistic motivations were also described as a vocational drive.

> "*[A]n integral opportunity to develop themselves and expand and learn and do they do that? Or do they take it on as a routine task, a job?*" (R19).

Interestingly, this sub-theme also linked to sub-theme A2.6 (extrinsic motivation).

> *"[F]ocus on innovation and creativity for the reasons you might imagine – discovery and the patenting of ideas, creating new products, meeting social requirements through discovery and so forth"* (R09).

However, the contrast between altruistic motivations and extrinsic, (or, selfish) motivations was noted. For example, the ability to associate oneself with a world-changing project (involvement with the Large Hadron Collider was used as an example) was seen as potentially beneficial for the entire world and simultaneously for oneself as *"[it] will have a major impact either for world or for personal economic gain"* (R23). One respondent commented on national pride as a strong motivational force:

> *"[E]ven though the country is difficult, we love the country, so I came back to Brazil and I knew I had to build something*" (R30).

Based on these findings, it is proposed that worldview (or, altruism) is a positive driver of BRP. Individuals that seek to contribute to society and have humanistic intentions may be more likely to produce radically innovative research outputs.

4.4.1.2.5 Sub-Theme A2.5: Extrinsic Motivation

Extrinsic motivation refers to motivation that is driven by external factors such as financial return. Many respondents noted that such motivators generally do not hold the same effectiveness as intrinsic factors. Respondents cited potential extrinsic motivators such as, "*reputation*" (R17), "*ambition for income ... or power*" (R22) or "*personal economic gain*" (R23).

> "*Some people work for money, a lot of people in academia work for academic glory*" (R29).

Conversely, many respondents also strongly asserted their preference for intrinsic motivators and their superior capability in generating research breakthroughs. This shows a link to sub-theme A2.1 (intrinsic motivation), although at the opposite end of the motivation spectrum. It is also noted that the notion of 'academic glory' may be a product of the mean age of the sample (73.5 years). Based on this finding, it is proposed that some extrinsic motivators may be positively drivers of BRP. Individuals that are motivated by extrinsic factors such as money, power and respect may be more likely, in some cases, to produce breakthrough research outputs. Proposition A3, related to the relationship between innate ability and BRP, is now discussed.

4.4.1.3 Proposition A3: Innate abilities such as intelligence and perceptiveness are positive drivers of BRP

Respondents were not asked to comment on innate ability directly. However, frequent responses that referred to intelligence, track record and perceptiveness were recorded. This suggests that 'innate ability' may be an internal driver of BRP. Table 15 lists the sub-theme

associated with innate ability, below.

Table 15: Innate Ability (sub-themes)

Theme	Theme Title	Key concepts	Respondents
1	**Intelligence**	ability, skill, creativity	R8, R10, R15
2	**Track Record**	previous success, capability, competence	R3, R21, R22, R23
3	**Perceptiveness**	bigger picture, systems, holistic insightful	R2, R14, R20

4.4.1.3.1 Sub-Theme A3.1: Intelligence

Intelligence is defined as an intellectual aptitude that is evidenced by exceptional conceptual ability.

> "*We look for people who have ideas, who can explain their ideas clearly and who are able to get under the surface of things and explain technically what innovations are needed and why something works or why something doesn't work. So, it's a combination of creativity and breadth and depth of understanding*" (R08).

Individuals who are "*bright*" (R10) and "*intellectual and conceptually agile*" (R15) are more likely to produce BRP. Such individuals are described as "*[having] a mind that can integrate new and previously unfamiliar things into their conceptual framework*" (R15). It is worth noting however, that intelligence was seen to be linked to HCI, particularly education. Individuals that are highly educated are more likely to be perceived as intelligent. Based on these findings, it is proposed that intelligence is a positive driver of BRP. Individuals that have highly developed creativity, and skills and abilities related to identifying and exploiting innovative research opportunities may therefore be more likely to produce breakthrough research outputs.

4.4.1.3.2 Sub-Theme A3.2: Track Record

Track record, or record of previous successes was also cited as a characteristic of individuals that are likely to produce BRP. Track record is not considered an innate ability but rather, an

outcome of innate abilities such as intelligence and perceptiveness. Track record is defined as "*past work that demonstrates their training, skill, and creativity*" (R23).

> "*The first thing you look for is a record of accomplishments. The best predictor of the future is often the past*" (R21).

This sub-theme may be linked to that of sub-theme A3.1 (intelligence) but is differentiated in that refers to an individual's ability to maintain a stable level of exceptional productivity. "*You look for people who have a reasonable track record of having produced good science*" (R03). It was noted, however, that this prior track record must be of an exceptional nature:

> *"[A]chievement that isn't just one more brick in an edifice that everybody understands and is working on, but an achievement that is off the beaten path or takes a different perspective on things*." (R22)

Based on these findings, it is proposed that a track record of previous success is a positive driver of BRP. Individuals who have previously exhibited skills, abilities and competencies that are prerequisites for producing breakthrough research outputs may be more likely to reproduce these effects, perhaps more so than their contemporaries.

4.4.1.3.3 Sub-Theme A3.3: Perceptiveness

Perceptiveness is defined as the ability to 'see the bigger picture'. It is also described as the ability to understand problems from a macro and micro perspective.

> "*It made it possible for me to have a much bigger impact in the field that I would have otherwise … and the reason was that having worked in a very small experiment, where I had almost no help, I had to understand almost the entire experiment in every respect and see how it all fit[ted] together and how important every piece was to making it work … and ended up having significant impacts in many different locations*" (R14).

Some respondents referred to the usefulness of working on large projects and having to understand a broad range of working components related to the project, many of which required in-depth understanding of a variety of different fields of expertise. This broad, cumulative

knowledge and experience, referred to as "*a flat competence*" (R20) helps individual researchers to maintain a comprehensive and multi-disciplinary understanding of research problems.

> "*My interest tends to sort of point to a bigger picture part of what I do*" (R02).

> "*I think a very important ingredient in my view of success for a leader in any kind of large enterprise is that he or she should try to understand all aspects of that enterprise and view it as a whole … have responsibility or vested interest in every aspect*" (R14).

Based on these findings, it is proposed that perceptiveness is a positive driver of BRP. Individuals that adopt 'big picture' or holistic thinking processes may be considered more insightful than their contemporaries and may therefore stand a greater chance of successfully producing breakthrough research outputs. Although innate abilities such as intelligence and perceptiveness were cited as important contributors to BRP, it was also noted that these alone are not sufficient. A balanced combination of abilities and skills, supportive environments and strong motivations is more likely to produce BRP than any one of these factors alone. Proposition A4, related to the relationship between technological propensity and BRP is now discussed.

4.4.1.4 Proposition A4: Open technological orientations are positive drivers of BRP

For the purpose of this study, the term technological propensity is defined as the extent to which individuals take advantage of new technological and methodological opportunities that offer significant economies of scale. Examples of these technologies or methodologies include crowdsourcing and crowdfunding. These can be used for data collection (Torr-Brown, 2013), research funding (Palmer & Verhoeven, 2016), data analysis (Goodman, et al., 2013), collaboration (Stieger, et al., 2012) and complex problem solving (Callaghan, 2015a). For Callaghan (2014a), these new technologies and methodologies offer significant opportunities in addressing 'catastrophic events', such as outbreaks of disease and natural disasters. They may also offer significant scale advantages. Inputs from large numbers of people may reduce time frames and costs significantly to the point where finding 'real-time' solutions to problems may be viable.

To assess technological propensity amongst qualitative respondents, a series of interlinking questions were asked. Some probing questions were also used, where necessary. Given the above definitions and descriptions, the purpose of these questions was multi-fold and includes the following:

- To investigate the extent to which new technologies and methodologies have been used to generate radically innovative research breakthroughs in the past.
- To assess renown innovators' opinions and views on the potential of new technologies and methodologies for future research.
- To explore the role of scientists and researchers during catastrophic events.
- To explore respondents' sentiment toward real-time dissemination of information, data, expertise and funding.
- To explore respondents' sentiments towards using crowds of non-experts to generate solutions to problems usually left to highly trained scientists.
- To explore the extent to which respondents would trust new technologies and methodologies such as crowdsourcing and crowdfunding to solve problems.

Six sub-themes related to technological propensity emerged from qualitative data. These include i) open orientation, ii) crowdsourcing, iii) crowdfunding, iv) technology use, v) role of management/acceleration and vi) journal publication perception. These are summarised in Table 16, below.

Table 16: Technological Propensity (sub-themes)

Number	Theme Title	Key concepts	Respondents
1	**Open Orientation**	Global involvement, sharing data, user innovation, big data, incentives	R03, R07, R09, R10, R16, R26, R30
2	**Crowdsourcing**	Information, knowledge, data, expert knowledge	R01, R03, R05, R07, R08, R11, R12, R13, R16, R26, R27,
3	**Crowdfunding**	Resources	R01, R11
4	**Technology Use**	Technology, speed of response, real-time	R01, R03, R08, R09, R29
5	**Role of management/acceleration**	Accelerating innovation, free expectations, management	R01, R03, R09, R10, R11, R13, R14, R15, R21, R22, R28, R29
6	**Journal Publication Perception**	Pro-publication vs. anti-publication	R03, R04, R05, R07, R08, R09, R11, R12, R14, R15, R16, R20, R21, R22, R24, R26, R27, R29, R30

Each of the sub-themes listed in Table 16, are now discussed with reference to quotes from interview transcripts. A discussion on open orientation now follows.

4.4.1.4.1 Sub-Theme A4.1: Open Orientation

Open orientation refers to a propensity, or willingness to try new things. Open orientation also refers to an inclination to share, collaborate, communicate and cooperate. Cross and multi-disciplinary collaboration was cited as an imperative driver of BRP. However, some respondents did not exhibit a propensity to try new things. These respondents alleged that tried and tested methods of scientific research should not change too radically, nor too often. However, these respondents made up only a small portion of the sample.

"*We should work in a more cohesive way. We must learn to cooperate*" (R30).

One of the interview questions posed a hypothetical 'global catastrophe' and asked respondents how best to address such a situation. Key words such as 'openness' and 'collaboration' were mentioned frequently. The importance of sharing data, working with researchers from across

the world and from different disciplines, was also considered imperative to address these types of problems.

> "*Globally, we have the opportunity and the mandate to use the knowledge… sharing that information is part of the social responsibility*" (R09).

The importance of openness was also substantiated by references to the potential drawbacks of not sharing data and collaborating.

> "*One of the things that happens very often in epidemics is that you get some researchers and public health officials [who] just want to control the data themselves, they don't want to share it. Sometimes they don't want to admit that there's an outbreak or perhaps they want to hang onto the data so that they can publish first. Now, officials have realised that its actually much to their benefit to share the data, samples and so on, as soon as possible and that could help later on*" (R03).

> *"The question is how do we keep it [knowledge] all open so [that] it's not so controlled. Otherwise we will not solve the challenges of new and emerging diseases or crop failures. Human society demands that we have that capability of learning from the past and using it in new ways*" (R09).

> "*You have to be able to and transfer knowledge. So, we need global… Anyone that can collaborate … PhD or academic is a good sign but it could also be a clever person who sits in their garage and develops something … we shouldn't neglect people who didn't have a formal education … have to stimulate them because the solution may come from them* (R10).

User innovation is a fundamental component of open innovation (Chesbrough, 2003a, von Hippel, 1994). One respondent provided a detailed account of his involvement with a user innovation-inspired online platform:

> "*They had this idea that there were many innovations – in medicine and in health care, not so much in finding a cure but in learning how to cope and treat problems – that came not from the doctors or the researchers but from the patients themselves. And for the*

simple reason that they were every day faced with a problem and they had to find a way to alleviate their problems. And very often they came up with really innovative solutions. And unless there was a group that they could share it with, no one else could find out about it. And the one example that I heard [of]when I first got involved with it was about a child who had very severe muscular dystrophy to the point where she really couldn't manage to get up off the ground, she could sort of crawl around on the ground, but she didn't have the strength to get up off the ground. And her parents had the idea, well maybe if they could tie some helium balloons to her, maybe she could get up off the ground and then she would be able to exercise her muscles because exercising the muscles is key to helping overcome those symptoms of dystrophy. And I thought that was fantastic" (R03).

Another respondent recognised the requirement for real-time solutions in scientific research but claimed that it was "virtually *impossible".*

"If you get all of that information dumped on you … there's misinformation, partial truths, etc. that you have to sort through and it's virtually impossible to sort through those in real time. The retrospective and the processed version of that is much more informative" (R07).

One respondent with a similar perspective advocated for the use of new Big Data analyses which have the capability to sort through significantly large volumes of data using specialised data analysis algorithms to extract the most pertinent data:

"*Cancer [research] makes more use of Big Data probably than any other disease area because of doing very extensive and detailed genomic analyses … So, we have the 'genomic data commons' and we have thousands of cases that have been carefully analysed… use computing and machine-learning to look at these large databases and we can actually find things that otherwise wouldn't be recognisable patterns*" (R26).

Overall, most respondents displayed high levels of open orientation, agreeing that "*you'd have to have really good communications. You can't just have a bunch of scientists saying do this, do this, do this*" (R16). Based on these findings, it is proposed that open orientation is a positive driver of BRP. Individuals that are openly oriented may be more likely to subscribe to the

importance of 'global involvement', the sharing of data and knowledge, user innovations and the potential of widely distributed or big data to enhance innovative research productivity. Such individuals may therefore be more likely to produce breakthrough research outputs.

4.4.1.4.2 Sub-Theme A4.2: Crowdsourcing

Crowdsourcing and open innovation were found to be closely linked. References to crowdsourcing were more specific to methods of data aggregation, collection and subsequent dissemination for further analysis. The use of incentives, data and information sharing, and the importance of expert knowledge were frequently cited, as shown in the following two responses.

> "*First of all, I'd need the data*" (R11).

> "*You need to find out as much as you can about it as quickly as you can*." (R16)

A probing question was used to further investigate crowdsourcing propensity. This question was asked with an accompanying description of crowdsourcing and open innovation. Some respondents reacted negatively to these. Others however, associated crowdsourcing with as incentives, as a way to foster data aggregation and sharing, particularly in health research.

> "*Well, we do support some research that involves crowdsourcing and there is also some research where we give prizes, so that different groups of people can simply come together and say I want to make algorithms – usually it's with information available through the internet – algorithms for making diagnoses, that are more efficient than what we currently have. So those are [the] kinds of things that we do* (R26).

When faced with the question of global catastrophes, most respondents agreed on the immediate need for data and knowledge sharing and dissemination. "*I would rush to find out what information was available"* (R05). Respondents also showed awareness of the need for critical expert knowledge in the case of catastrophic problems:

> "*You would need to have people who are genuinely understanding of the problem … put them in the room with as much data as possible*" (R07).

Other respondents replaced the word 'room' in the above quote with "*communication, coordination and [getting] information distributed … in real time*" (R12). The use of computer technology as a new methodology or platform, was also cited as a mechanism through which information distribution may be enabled.

> *[G]et information very quickly about where the problems are so that people who are then working on what to do about it at least are well informed about what the problems are and where they're happening*" (R08).

> "*Devise a way … a forum of some sorts where that expert knowledge gets coalesced and processed and then communicated*" (R16).

One respondent succinctly described 6G innovation, as defined by Callaghan (2014a), by referring to the importance of new communication technologies to disseminate knowledge as quickly as possible, to find real-time solutions.

> "*So, real-time solutions are coming from open access. Work that's coming out now, where researchers are working across the world, have been making available in real-time the sequences of Ebola virus strains. So, the sharing, creation of virtual networks for surveillance has turned out to be [an] extremely important tool for the management of outbreaks. The key here is to combine the availability of open sharing of information. Where people can actually track and monitor in real-time a disease outbreak. So, I'm very optimistic about the ability of public health systems to respond in this kind of way. Of course, it's totally reliant on the availability in sites where the diseases take place, where the diseases take root, it's important to have the technology available which is the laboratory technology plus the IT infrastructure so that we can participate in these kinds of networks*" (R12).

Social media was discussed as a potential method of data and knowledge aggregation and dissemination. But social media was more commonly referred to as a potential "*short-term solution*" (R07) for the collection of knowledge and data, rather than for its analysis.

"*What you would really want to do is get information from a huge area and compile what they saw"* (R01).

Some respondents however, noted the differences in their understanding of groups and crowds, differentiating between expert and common knowledge.

"*I'm not a big believer in crowds. I am a big believer in groups and even independent groups collaborating. So, we ... you know ... genetics, is the perfect example where people doing good work, mapping genes under certain circumstances and different species have very effectively collaborated in terms of advancing the science dramatically because no one group by themselves is ever going to have enough time, energy and machinery to do everything that needs to be done. I know people in data sciences have done the same thing – they create new data mining techniques, new statistical approaches – [and] they open those equations, so people can be able to test them and validate them and then once validated, they can improve upon them and they can make suggestions. So, there are areas where informed thoughtful people can contribute, and everybody can benefit, so I'm a big believer in that. I'm not a big believer in the wisdom of crowds"* (R27).

The importance of expert knowledge from "*around the globe*" (R16) is considered critical. Most respondents agreed that the knowledge of experts is required to address catastrophic events.

"*So, we have to gather knowledge; critical knowledge*" (R16).

"*You have to have the best possible team and that's going to depend on who the good people are and getting out in the field and just addressing this*" (R13).

"*Identify the best expertise you can and prevail upon those people to you know come together. So that's where you need to gather information. So, you need get experts together*" (R16).

"*Identifying the best experts and experts who are really good at communicating and experts that have … open-mindedness and an ability to work with other people and have them somehow linked up in an effective way"* (R16).

Many respondents identified the importance of expert knowledge and input. However, most respondents failed to identify the mechanism through which experts could connect, communicate and collaborate. Moreover, while the importance of expert knowledge was frequently cited, these are in direct contrast to previous statements regarding the importance of not adhering to or relying on conventional wisdom. This schism underlies 6G innovation theory. Some respondents reacted negatively to open innovation and crowdsourcing. These negative responses further highlight 6G innovation theory. Even though new technologies and methodologies that offer scale advantages do exist, their adoption is inhibited.

"*We are not faced with the problem of insufficient information, we are in fact [faced] with the problem of too much information. There are too many primary sources, that is, primary reports of experimental work and so forth and too few view-level articles and reports. It's an issue of the organisation of information"* (R05).

"*You don't really need crowdsourcing to be honest. You know crowdsourcing can be a good way to do stuff but in the case of disease outbreaks I don't think you need crowdsourcing at all"* (R03).

"*So, in my area I think it's ridiculous, quite honestly. Because the crowd is not smart. Wisdom of the crowds? There's not a lot of wisdom of crowds. We just elected an idiot named Trump to the presiden[cy] of the United States, that's a crowd phenomenon*" (R27).

These quotes show that in some cases, the notion of open innovation or crowdsourcing may be viewed in a negative light. This may suggest an unawareness or an unwillingness to adopt new technologies and methodologies that are somewhat unconventional. In other words, this may be a sign of low technological propensity. Positive responses however, seemed to outweigh those that were negative. Based on these findings, crowdsourcing is a positively driver of BRP. Individuals that are open to the concept of knowledge and data sharing, over the Internet, particularly expert knowledge, may be more likely to produce breakthrough research outputs.

4.4.1.4.3 Sub-Theme A4.3: Crowdfunding

An interview question that asked respondents to name alternate methods of research funding, was used to investigate crowdfunding. Some responses captured the need for unconstrained resource availability, particularly in the case of catastrophic events.

> "*How to get the best resources to certain places affected by the disaster – that's always a big problem"* (R11).

> "*It would require a commitment from a group of people or an institution or a government that has sufficient resources to throw it at it* (R01).

The subject of research funding and its relationship to innovative research, did generate significant debate. This theme is discussed further in Section 4.9. Based on these finding, it is proposed that the use of crowdfunding is a positive driver of BRP. Crowdfunding relates to the availability of resources. An increase in the availability of resources may increase the probability of producing breakthrough research productivity.

4.4.1.4.4 Sub-Theme A4.4: Technology Use

The use of new technology is considered crucial to produce BRP. New technologies were also cited as a way to address catastrophic events, cut resource costs, to foster communication and collaboration and to disseminate knowledge, data and information.

> "*We're so well interconnected these days. People are much better at talking to each other around the world than they used to be and it's possible to mobilize much more quickly*" (R29).

> "*Does technology help? Of course. It saves a lot of time. And so, the work tends to be much more efficient*" (R01).

New technologies may offer enhanced efficiencies, economies of scale and real-time solutions or responses. The Internet was cited as an example of a new technology that may offer these advantages.

"*The use of computer technology to get information very quickly about where the problems are so that people who are then working on what to do about it at least are well informed about what the problems are and where they're happening*" (R08).

"*You want to move very quickly. I think surveillance is very important when it comes to any sort of infectious diseases*" (R03).

Some references to newer, emerging technologies such as artificial intelligence (AI) were also made. Big Data and Big Data Analytics also fell into this category.

"*I'm looking forward to the time when knowledge…(artificial) … and the gathering of information which then has algorithms that interpret it from raw data into hypotheses and maybe even knowledge will help us with solving a human disease on an individual basis as well as a community basis*" (R09).

Based on these findings, it is proposed that technology use is a positive driver of BRP. Researchers that make use of certain new technologies may have advantages over their contemporaries, owing faster response times, greater availability of knowledge and the ability to disseminate information and knowledge in real time. As such, technology use may prompt an increase in the likelihood of producing breakthrough research outputs.

4.4.1.4.5 Sub-Theme A4.5: Role of Management/Acceleration

Another interview question asked respondents to describe what they believe is the role of management in scientific research. The question also asked if it is possible to accelerate the rate at which scientific breakthroughs are made. A broad range of different responses were recorded for this question.

"*I think that good management can foster creativity and the possibility and probability of breakthroughs*" (R22).

"*It's very important to be able to amass scientific power quickly*" (R29).

Most respondents agreed that the role of management in scientific innovation is to ensure effectiveness and efficiency. However, over-management may inhibit creativity and stifle innovation. This is common in cases where management is too narrowly focused on certain goals and objectives.

> "*I don't think as a driver one has to try to impose specific deadlines or impose upon the fields of research that they need to accelerate because generally speaking for top researchers in any field, they know they're all racing to beat somebody … If they could, they're all moving pretty darn fast – they go as fast as they can. And if they had more resources they could move faster or broader, etc. up to some point where they saturate. So, I think actually for really good researchers, what's more important is that they have strong support*" (R14).

In discussing potential breakthrough acceleration, one respondent drew parallels between academic scientific research and the burgeoning software industry.

> *"[A] significant overlap in the management between scientific management and a pure research and management in the software industry. They have shorter deadlines, they're more goal driven. In some ways, you're managing people to do technical innovation and push the forefront of technology and develop new ideas and it's not so different from what we do here where we're pushing scientific innovation at the forefront of science. I think we can learn from some of the management innovations happening in those areas. Academia is not the same as a software start-up but there are things that they do that I think we can learn from"* (R21).

The difference between fostering, and accelerating innovation was noted. Management does have a role to play in fostering innovation, but misguided attempts to accelerate innovation could be detrimental to the scientific process. This is especially true of the "*translation from fundamental science into achievable goals*" (R09). The objectives of scientific research also must be taken into account. The management of scientific research will differ depending on if it is conducted for academic purposes or to achieve organisational objectives. There was noted disagreement on whether innovation could be taught or not.

"*You can teach most people innovation if they're charged to do so*" (R09).

"*You cannot teach innovation, innovation has to come from the inside. Innovation – you can nurture, you can help to stimulate innovation … Artificially you cannot stimulate it"* (R10).

The unintentional creation of "*knowledge silos*" was cited as a potential negative outcome of scientific research management. To avoid this, the role of management should be to foster innovation by stimulating creativity, collaboration and communication and removing barriers to innovation. Essentially, management should seek to create a working climate that is conducive to innovation.

"*Create the environment in which those happen, rather than creating boundaries to stop that from happening*" (R21).

It was also noted that managers need to have a thorough understanding and broad knowledge of the research they are managing.

"*[C]reative and broad-minded people [that can] inspire others to do it. Not so much telling people which project is most valuable but providing an environment for them to make the choice*" (R22).

In some cases, management may introduce barriers to innovation, rather than remove them. Parallels were drawn between cases such as these and journal publication, both of which may sometimes unintentionally inhibit innovation.

"[A]ny really new ideas will appear unappealing to the manager … so you get feedback from the publication system. But most people react to that by sticking to fairly safe topics" (R29).

This sub-theme (the management of scientific research) linked to work climate and motivation. Motivation to generate research breakthroughs is fostered through a supportive work climate. Supportive climates, in turn, are created by supportive, innovative, encouraging and broad-minded managers. This link between "*personal encouragement*" and "*communication*" (R27)

is critical in fostering innovation, creativity and ultimately, BRP. However, the differences between academic and organisational objectives may introduce difficulties in the management of motivation and climate.

> "*In the world of business there is an unfortunate expectation that your work will lead to an immediate result, an immediate benefit. And that is often hard to guarantee. They really do need to see a result quicker than we can guarantee it and they often aren't interested in a longer-term view, and that is unfortunate, but that's the way the world is. So, what they either do is, they just pump more money into [it] hoping for a result that suits them better, or they remove the funding, saying how can we justify this to our stockholders?*" (R01).

It is suggested that the way to overcome these differences is to "*be much more open and allow different ways of doing things*" (R11) and to *"give them independence; often they will be very innovative and think in ways quite different*" (R15). To accomplish this, managers should maintain broad and open perspectives.

> "*[U]nderstand that it's their job to enable the people who are doing research and to keep them as free as possible of anything other than doing their research*" (R04).

Some respondents reacted negatively to the notion of scientific research management. Management may, in some cases, stifle creativity and constrain innovation

> "*I think management in general does not have a very good idea of what research is all about. I think If anything management tends to slow down breakthroughs*" (R03).

> "*The more management, the less innovative or competitive, to my experience. My preference would be to stay away from managers as much as possible*" (R13).

> "*Right now, we're being way over-managed … I mean they have so many rules and regulations … So, we're being strangled now*" (R28).

Some respondents were also resistant to the idea of accelerating innovation, claiming that accelerating scientific innovation is impossible.

"*Just by thinking that you can accelerate it – I think, tells you that you don't understand something about the nature of the research process*" (R03).

"*Absolutely not. This is silly. Ask an artist to accelerate the work he spends on a painting? Would that improve the result? A good publication is a piece of art*" (R13).

These negative responses however, only formed a smaller component of the sample. Based on these findings, it is proposed that management/acceleration is a positive driver of BRP. The use of management techniques that encourage technology use, the acceleration of innovation and that are free of expectations may enhance the probability of researchers producing breakthrough research outputs.

4.4.1.4.6 Sub-Theme A4.6: Journal Publication Perceptions (Pro-Publication vs. Anti-Publication)

Respondents were asked for their thoughts on the innovativeness of journal publications. This question was asked to determine respondents' perception of innovativeness in academic research. Respondents were also asked if they had ever experienced resistance from journal publications when trying to publish innovative research. Respondents generally tended toward either pro-publication, or anti-publication. Each of these are discussed respectively, as follows.

Pro-publication

Some respondents indicated that they had not experienced any significant forms of resistance from the academic publishing system. These respondents, referred to here as 'pro-publication', also tended to agree that the academic publishing system is satisfactory and not overly conservative or biased.

"*By and large I've had little problem publishing my work. And I probably benefited from the publications a lot more than I was ever hindered by it"* (R04).

"*The papers I wrote were fairly treated*" (R05).

"*As long as you can explain the relevance of the work, I think people are quite open to new ideas*" (R08).

"*No resistance at all from the scientific publication*" (R09).

However, pro-publication respondents did suggest that publications tend to have a "*healthy dose of scepticism*" (R04). This is necessary to avoid the publication of low-quality research. Generally, pro-publication respondents agree that publication needs to "*strike some kind of balance*" (R05) and tend to do this well.

"*If the idea or question hasn't been formulated in the literature, they're a lot more reluctant to let that through. And this is because [if] you do come up with something new you are to be the advocate and to provide proof. There is certainly a lot of hokum out in the literature. So, I think that there is reason to question the review process*" (R07).

"*I wouldn't say that there is opposition to innovation. I would say that there is opposition to speculation without evidence, but that's not necessarily a negative thing*" (R26).

Although pro-publication respondents may not have experienced rejection or resistance to their own work, some did acknowledge that publications may reject research out of hand.

"*Obviously, you don't want rejection. But at the same time, you don't want the literature to be full of a whole of lot of vaguely formulated research. So, I think by and large the major journals* – Science, Nature – *they do a reasonable job*" (R05).

Pro-publication respondents frequently stated that publications must maintain high-quality standards with "*solid editorial policies*" and "*robustness*" (R16). Publications that are not robust enough will inadvertently be of a lower standard, or quality. The difference between incremental and radical innovation was also noted. Some respondents expressed the view that journal publications should not publish radical innovations and should instead focus on publishing incremental innovations.

> "*They don't actively discourage innovative new ideas or anything, but their mission is not construed as a place where you publish something that you would think is really super noteworthy and novel*" (R16).

Maintaining high levels of scientific rigor may help to avoid rejection. Some pro-publication respondents noted that much of their research had only been published after years, or even decades of experimentation and study.

> "*We have these giant projects; these things have been planned for years*" (R14).

> "*Fairly, I only go to journals when we have results. And the journals have never failed to publish anything we've submitted"* (R14).

> "*In our case, we ended up doing a key experiment that was so convincing that everybody accepted it"* (R03).

> "*The editors of that first discovery were very interested but very critical and they demanded increasingly the description of the work, why it worked, making sure we were absolutely correct"* (R09).

Some pro-publication respondents argue that journal publications are "*willing to publish articles of mediocre quality too often*" (R21). These respondents suggest more stringent guidelines are required. This matter was often mentioned in conjunction with 'information overload', and a generally negative attitude towards open access and electronic journal publications. Respondents of this view suggest that "*you can publish anything today"* (R27).

> *"[O]ne of the problems there was that people were overwhelmed with articles there because literally anything can be published, there's a lot of junk journals out there*" (R27).

Similarly, 'for-profit' journals were seen as problematic amongst some respondents.

> "*[The] business imperative often ends up creating situations where a discovery or paper will get published and the emphasis is to try to highlight the novelty and the unexpectedness; the front-edge rather than the solid foundations*" (R16).

Essentially, pro-publication respondents maintain that journal publications are sufficiently restrictive or are not restrictive enough. In both cases, these respondents advocate thorough and rigorous science that leaves no room for error. Information overload should be mitigated. Journal publications that wish to maintain high standards of quality should only publish research that is scientifically rigorous. Scientific progress is important and encouraged but this is best achieved by incremental means, rather than radical means. Radically innovative research is also encouraged but only if it is backed by years or decades of extensive experimentation and study. Anti-publication respondents are now discussed.

Anti-Publication

Respondents that are not pro-publication are classified as anti-publication. These respondents expressed the view that journal publications are generally resistant to new ideas and radical innovations. Some claimed that such high levels of resistance are substantiated by continual efforts to reduce the publication of "*nonsense*" (R05).

> "*Everybody experiences resistance, it just depends on the journal and the quality of the editors; their openness to new ways of thinking. And so I might say that one's experiences vary widely depending on the journal. Some journals are very averse to new things that don't conform to pre-existing preconceptions, others are very open even to the extent of being overly open by publishing material which is new and exciting, it seems, but ultimately not well founded experimentally. So, it moves all over the spectrum. It's a very subjective point of view and I wouldn't blame academic journals for that as much as other things*" (R15).

The overarching sentiment amongst anti-publication respondents is that radical innovations may be too difficult to publish with any level of certainty, and thus that resistance is justified, to an extent.

"*I think almost inevitably it's a lot easier to recognise high quality works that contribute to a paradigm and a process that's already well understood and just moves it the extra distance, or the direction at least that is well accepted, it's worth moving*" (R22).

"*People nowadays, people who had some kind of 'off the wall' idea will have some difficulty getting it published*" (R05).

Despite this, resistance to radically innovative research is sometimes unfounded and illogical. In some cases, journal publications may reject research that is radically innovative without sufficient justification.

"*In general, there's a lot resistance to totally new ideas*" (R07).

"*You're not supposed to contradict other people's work*" (R30).

"[R]eferees get angry at certain papers ... sometimes it's because the paper has something really new in it that upsets people" (R29).

Essentially, anti-publication respondents held the view that journal publication tend to favour incremental research. This may often be to the detriment of scientific progress and discovery. Some respondents claimed this resistance to innovation may even provide indication of research that is truly innovative. Some anti-publication respondents argued that peer-review panels and those reviewing articles for journal publications often "*don't understand*." (R10), or perhaps even "*resent it and reject it out of hand"* (R22).

"*I would not say that the system of publishing is working in the direction of discovery and innovation, at least, in my field*" (R20).

"*I tell young faculty all the time that if you really think what you've done is methodologically correct ... if it gets turned down more than two times ... I say you're onto something really big"* (R27).

"*We've gone on to make a number of other discoveries and most of those have received resistance. The natural peer-review system in most journals leads to that and if you go*

back to a lot of the major discoveries out there you'll find that the initial publications were in second tier journals because the people, when they submitted them to first tier, returned them" (R07).

One respondent noted the similarities between journal publications and funding agencies, in their unwillingness to support radically innovative research.

"*It's not just the publications, it's [that] the funding system is not prepared for something 'out of the box'. They would prefer to use the funding and resources for a project that's very incremental. They're only prepared to pay you for something that you already proved and that probably you know the answer to. And the journals are the same. They measure people from the past. How can you do something new measured by the past*?" (R30).

One of the few female respondents commented that "*it really is shocking to me how much resistance and part of it maybe is because I'm a woman. I hope not*" (R25). Most the sample comprised of male respondents. However, this quote does show a potentially serious problem that may exist in the case of academic journal publishing. Another female respondent noted a significant level of "*prejudice*" (R30) in the academic journal publishing system, not specifically towards women but to those researchers from developing countries.

"[T]here's a part of the publishing system that doesn't allow you to take risks. If you're in a good place [developed country] you can take risks, if you aren't, [developing country] you cannot take risks" (R30).

Anti-publication respondents cited the problem of 'publication pressure', both in terms of time and resources. Researchers may feel pressure to publish as frequently as possible which may act as a detriment to the quality of their research output.

"*Many young people will think they have no choice but publication, to rush to publication*" (R11).

The qualitative sample was primarily comprised well-established individuals, who have over the course of their careers seen dramatic shifts and changes in the processes of journal

publication. Many were able to draw comparisons between the state of academic publication in the past and present.

> "*In our time it was much easier, there was not the same pressure to publish*" (R03).

Another respondent mentioned how his research (first published in the 1960s) had experienced almost no resistance. This, despite the fact that he had gone "*against every single scholar who – just about – who had written on the subject"*. This same respondent suggested that "*today it would never be accepted*" (R24).

The use of online and open access journal publications was suggested as a potential remedy to the problem of publication resistance. "*You could always just put it on the internet*" (R05). Some respondents mentioned that the traditional format of journal publication was fast becoming obsolete in certain fields.

> "*At this point, most of us don't read articles in the journals anyway, we read them on the electronic boards*" (R21).

Electronic journals were also suggested as a form of pre-publication. This might be used either to verify or invalidate the findings of a paper prior to applying to more established and traditional publications. The ease of online publication was described as a relatively new development. Online publication could potentially provide significant advantages to researchers meeting high levels of resistance from traditional publications. Several anti-publication respondents praised the potential of open access journals as a method of gauging the quality of one's research.

> "*I am strongly supportive of the idea of putting information out there – open access. It's very expensive to publish open access but it's important to give your research visibility, to make it accessible to as many places and people in the world who can actually read it*" (R12).

However, the potential detriments of online publication were also mentioned.

"*This may not be so good because the communications are so fast and quick but there's less depth*" (R11).

Citations have become increasingly important for both universities and individual scientists. Anti-publication respondents referred to citations as an important aspect of the digital age in scientific research. Some respondents raised questions as to the efficacy and usefulness of citations.

"*We are metrics crazy, you can measure the number of times your article is downloaded. In the world of social media everything is far more open, and people are trying to promote themselves because this is what universities are now recognising; how many times your work has been cited. I think publication practices have change dramatically and there is definitely a push towards selling one's research in a way that one has a big story, a big punch attached to it, so you can get into the top scientific journals*" (R12).

"*A good paper isn't measured by citations*" (R11).

Anti-publication respondents agreed that citation and indices may be useful. However, making decisions "*based on citations*" (R11) may be problematic, since citations may not be indicative of innovativeness. Some anti-publication respondents claimed that journal publication is outdated. Specifically, respondents in the field of computer science noted that they had very rarely experienced resistance. Computer science, as a field "*is a lot younger … than other scientific fields so there's less prejudice against anything new*" (R04). Another respondent in the statistical sciences made similar remarks.

*"[Computer science has] moved away from conventional publishing. Mostly information is put out in conference*s (R08).

"[*U]nusual ideas and haven't gotten very far… some of them just abandoned the system. Maybe they won't publish at all. Maybe they'll just write in their own notebooks and give a talk every once in a while*" (R29).

These quotes show that traditional journal publication may, in some cases be on the decline. New methods of data, information and knowledge sharing, and dissemination have begun to

emerge and take root. In summary, anti-publication respondents generally tend to be of the view that journal publications are too resistant to radically innovative research. Because of this, important research may become lost or go unpublished. To counteract this, some have turned to unconventional methods of dissemination, such as online or, electronic journals.

The measurement of journal publication perception is important because it provides insight into the views and opinions of respondents regarding the state of academia. In broad terms, respondents were classified as being either pro-publication or anti-publication. Pro-publication respondents generally tended to express the view that the journal publication system is healthy. These respondents had often not experienced rejection from journal publications but tended to agree that academic research should be primarily concerned with incremental innovation, rather than radical innovation. On the other hand, anti-publication respondents generally tended to express opposing views; that the journal publication system is flawed. These respondents reported frequent rejection from journal publications and that journal publications are often overly-stringent in their acceptance policies. These findings are summarised in Table 17, below.

Table 17: Journal Publication Perceptions

	Description	Key concepts
Pro-Publication	• Respondents that have not experienced rejection from journal publication • Respondents that think that journal publications should be critical of radically innovative research	• Journal publications should publish only high-quality, scientifically rigorous research • Journal publications are not a place for radical innovation, rather for incremental innovation • There is resistance to radical innovation, but it is necessary to keep the high-quality of published research • In some cases, there is not enough resistance; there should be higher levels of stringency in selection for publication
Anti-Publication	• Respondents that have experienced rejection from journal publications • Respondents that think that journal publications are too critical of radically innovative research	• There is too much resistance to innovation in journal publications • This is often illogical and may be attributable to discrimination (gender, education or nationality) jealousy or conventional wisdom • In this way, system of journal publication is similar to the system of funding agencies since both are risk-averse and prefer incremental rather than radical ideas • This has changed over time. In the past it was easier to publish radical ideas, but it is more difficult today. • Advocate for online and open access publication or conferences rather than journals for new, radical research

Based on these findings, it is proposed that journal publication perception is related to BRP. Individuals that maintain either anti-publication or pro-publication stances may be equally likely to produce breakthrough research. However, those individuals that maintain anti-publication stances are more likely to adopt unconventional modes of productivity, or publication, which may, in turn lead to a higher probability of producing breakthrough research. Individuals that maintain pro-publication stances may be more likely to conform to orthodoxy, which is averse to the requirements of radical innovation. It is stressed that journal publication perception does not strictly define BRP potential, but certain stances may be better suited to BRP than others. The links and associations that make up Proposition A, related to the internal drivers of BRP, are depicted in Figure 15 below. It is stressed that all relationships depicted in figure 14 are positive, given that these diagrams represent positive drivers of BRP.

These represent the model that emerges from the grounded analysis, discussed above, and which are discussed further in Chapter 6.

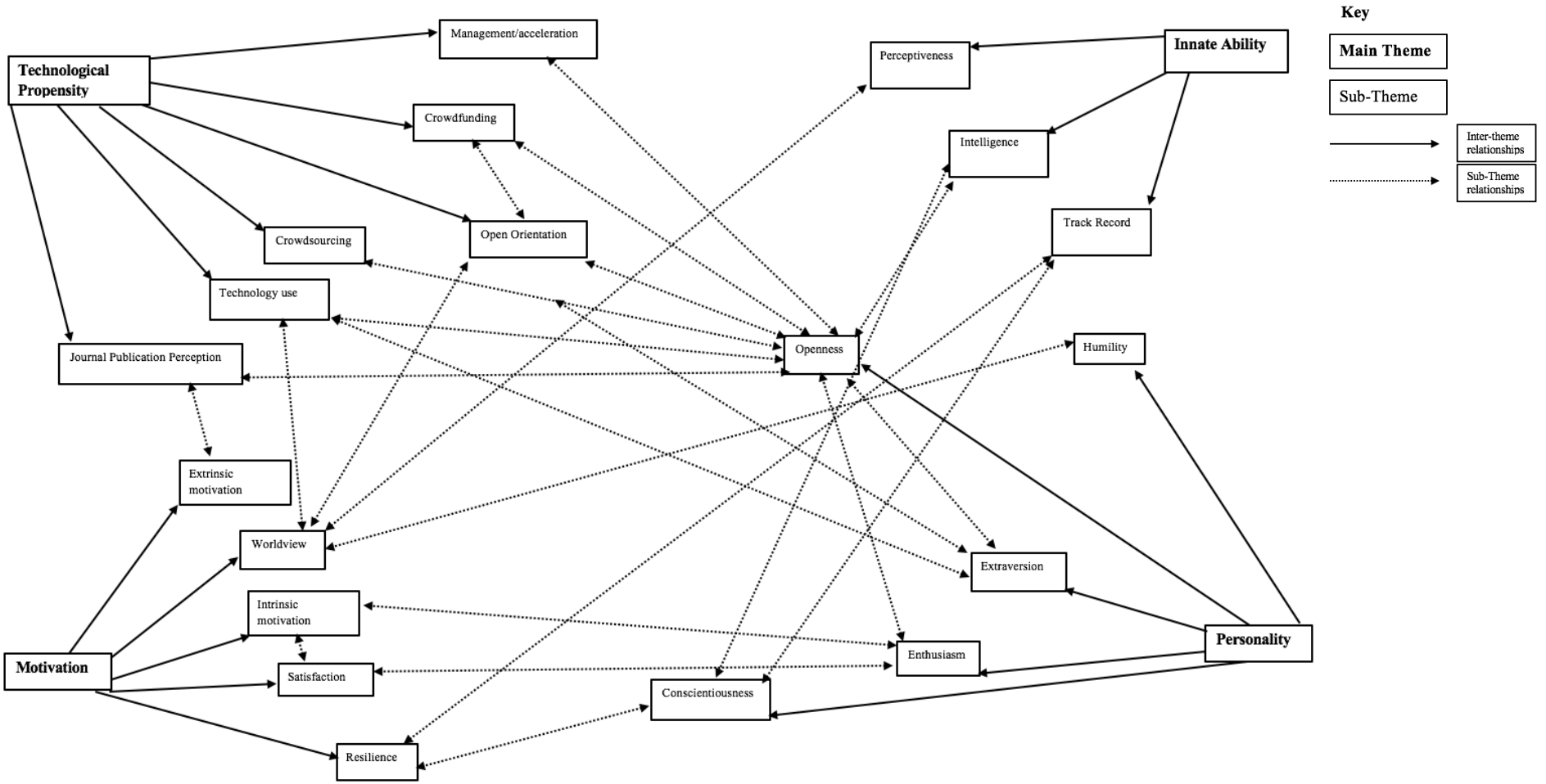


Figure 15: Internal Drivers of BRP

Having discussed the internal drivers of BRP, Proposition B, relating the relationship between external drivers and BRP, is now discussed.

4.4.2 Proposition B: External Drivers such as human capital investments, work climate and resource availability are positive drivers of BRP

External drivers refer to outside influences, or those that are not inherent to the individual, which may impact BRP. Based on qualitative analysis, these drivers include i) human capital investments, ii) work climate and iii) resource availability. Each of these is discussed in their relationship to BRP, as follows.

4.4.2.1 Proposition B1: Human Capital Investments in education, experience, support and cross-pollination are positive drivers of BRP

Human Capital Investments (HCI) is defined as the intangible assets such as knowledge, expertise, skills and values that cannot be separated from the individual (Blundell, et al. 1999). Three sub-themes pertaining to HCI were extracted from interview transcripts. These are summarised in Table 18, below.

Table 18: Human Capital Investments (sub-themes)

Theme Title	Key concepts	Respondents
Education & Experience	Background, education, early environmental support, background (nationality)	R04, R08, R15, R27, R30
Support	Family, mentorship, upbringing	R04, R18, R19, R22, R25
Cross-pollination	Multi-disciplinary, cross-discipline, ability to see the bigger picture (perspective), conventional wisdom	R03, R04, R05, R07, R10, R14, R30

Education and experience, support and cross-pollination are consistent through the parent theme of Human Capital Investments. The diversity of HCI (or, variety in education, training or experience) emerged as a common thread that tied these sub-themes together. While standard education, training and experience do indeed seem to contribute to later success, the variability, or *diversity* of these HCI inputs seemingly increased the potential of BRP. Each of these sub-themes is discussed below.

4.4.2.1.1 Sub-theme B1.1: Education and experience

Most respondents had been trained in the same field in which their breakthrough was made. This was viewed, by some respondents, as an advantage, since they did not need to "*start from scratch*" (R04). Others gave similar reasons.

> "*What had prepared me to ask those questions from an educational perspective was having been trained in epidemiology*" (R27).

> "*I certainly wouldn't have been able to do any of this work if I hadn't had that background … so I understood what the problems were. It was like a continuing story*" (R08).

Early environmental support also formed an important component of this sub-theme. Some respondents referred to their formative years, particularly their early education, experiences and exposure to ideas and ways of thinking, that would later heighten their interest in their area of study.

> *"[I]mmersing oneself relatively early in life in intellectually challenging disciplines… sharpens the mind and makes it prepared for moving in different directions later in life*" (R15).

Interestingly, one respondent referred to how she "*came from a poor background … my parents were not wealthy*" (R30) and conversely, how this was an important contributor to later success. Researchers from developing countries seemed to have different experiences compared to those from more developed countries.

> *"[U]sually when you finish your PhD, you go abroad and face all kinds of prejudice. And if you come from a rich background, you're not used to be[ing] treated like a second-level citizen. I spent all my life being treated as a second-level citizen so when I went to the United States, when they looked at me and they thought I was going there to work in next-door supermarket. I didn't care*" (R30).

This is referred to as a tension between academics of different nationalities. It links closely to sub theme 1.2, or that of Support. Based on these findings, it is proposed that education and experience is a positive driver of BRP. Individuals that have accumulated investments in education and early environmental support may be more likely to produce breakthrough research outputs later in their careers. Furthermore, differences in upbringing (such as nationality) may further positively contribute to BRP.

4.4.2.1.2 Sub-Theme B1.2: Support

Environmental support from formative years and into the later stages of a career was found to be an imperative contributing factor to breakthrough success. This is especially true in the case of respondents whose passions were recognised. Support from early social environments, including friends, family and educators is also important. Supportive parenting styles, in particular, were described as important contributors for breakthrough success later in life.

> "*I'm very much a product of my love of mathematics*" (R04).

> "*I've been doing that since I was 10 years old …[my] social environment … permitted me to spend my time studying*" (R19).

> "*A pair of parents who basically let me do whatever I wanted to do and encouraged me when I had crazy ideas that did not match with the rest of society, they encouraged me to keep on with those crazy ideas*" (R18).

This sub-theme also revealed the importance of independent behaviour. This links to sub-theme A1.4 (conscientiousness). Independent behaviour may stem from environments, actions and patterns of thought that are outside of the norm, during developmental stages. It was noted that such behaviour may help foster innovative thinking, if controlled and focused. One respondent attributed early success to:

> "*[A] meeting with President Kennedy and being told that I was one of the most promising young scientists in America−and that early recognition, I think, gave me confidence. I think that I could just follow my nose and not worry about what other people thought was*

most worth doing. And not worrying about whether there's immediate application to the work but to trust my instinct to do what's interesting and fun" (R22).

This sub-theme also links to sub-theme B1.3 (cross-pollination). Specifically, the ability to approach problems without conventional bias. Mentorship, or the guiding support of mentors and educators, was also cited as a catalyst for stimulating innovative thought.

"*I think that I had great mentors who also believed in these classical views but who pushed boundaries themselves*" (R25).

Based on these findings, it is proposed that support is a positive driver of BRP. Like education and experience, support relates to external supporting mechanisms that may aid researchers in the production of breakthrough outputs. Individuals with supportive familial structures and access to mentors may be more likely to produce breakthrough research outputs than their contemporaries.

4.4.2.1.3 Sub-Theme B1.3: Cross-pollination

The term cross-pollination is used to refer to the sharing of ideas, data, knowledge and information across different fields of discovery. This sub-theme emerged as an important contributor to innovation. It links to various other sub-themes including A1.3 (openness), A1.4 (conscientiousness), A3.1 (open orientation), B1.1 (education and experience) and B1.2 (support). Many respondents were trained in fields different to the one in which their discoveries were later made. These respondents who made discoveries "*in a different field*" (R03), were able to "*think differently than the way most scientists in my field do*" (R04). Those who "*changed methodology and field"* (R07) were strong advocates of the cross pollination of knowledge to stimulate innovative research output.

"*I changed methodology and field. The senior people said never do that, don't change. But I realised that if I didn't, I would do the same thing, the same incremental work*" (R30).

The ability to 'think outside the box', or to look at existing problems from a new perspective was shown to be an important contributor to solving complex research problems.

"*So, that interest in [the] multi-disciplin[ary] aspects of things has been throughout and its really fostered by the idea that when you want to solve a problem, you want to perhaps use something new, new capabilities to look at those old problems … and that's often where those new insights come*" (R07).

Interaction with other scientists, researchers and academics was also shown to foster creative and innovative thinking. Respondents that collaborated, or sought the advice, help and expertise of fellow academics were more likely to produce innovative research outputs. As a result of cross-pollination, respondents reported enhanced ability to 'see the bigger picture'.

"*When you work abroad, and you meet other people, other scientists with other education, other backgrounds, everything helped to develop your ideas*" (R10).

"*I built connections…. A reservoir of connections*" (R30).

"*It made it possible for me to have a much bigger impact in the field that I would have otherwise … and the reason was that having worked in a very small experiment, where I had almost no help, I had to understand almost the entire experiment in every respect and see how it all fit[s] together and how important every piece was to making it work … and ended up having significant impacts in many different locations"* (R14).

Several respondents also referred to the importance of not conforming to dogmatism of traditional research, or 'conventional wisdom'. In general, conventional wisdom was referred to as a negative influence and one that should always be scrutinised.

"*I did not know what I needed not to know. I had not read those textbooks and I think had I read those textbooks I almost certainly would have gone in the wrong direction*" (R05).

Based on these findings, it is proposed that cross-pollination is a positive driver of BRP. Individuals that engage in multi and cross-disciplinary knowledge exchanges may be more likely to adopt 'big picture' thinking and a s a result, reject conventional wisdom, which may be outmoded. As a result, such individuals may be more likely to produce breakthrough

research outputs. Proposition B2, related to the relationship between work climate and BRP is now discussed, as follows.

4.4.2.2 Proposition B2: Work climates that encourage collaboration and provide incentive and managerial support are positive drivers of BRP

Four sub-themes pertaining to work climate emerged from interview transcripts. These are summarised in Table 19 below and subsequently discussed in the sections that follow.

Table 19: Work Climate (sub-themes)

Number	Theme Title	Key concepts	Respondents
1	**Freedom**	constraints, exploration, structures, resources	R1, R3, R4, R5, R12, R14, R19, R23, R29
2	**Incentive**	reward, recognition, value, achievement	R1, R8, R9
3	**Collaboration**	cross-discipline, sharing, openness	R4, R5, R7, R13, R14, R15, R22
4	**Managerial Support**	structures, support, resources, mentorship	R7, R10, R14, R16, R18, R19, R21R23, R25, R26

4.4.2.2.1 Sub-Theme B2.1: Freedom

Respondents frequently cited the importance of freedom, in terms of freedom to explore new avenues, new problems and new areas of research, as well as financial freedom. It was noted that managerial structures that are conducive to freedom are imperative. Similarly, the importance of open-minded managers was noted. Such managers are referred to as those who foster creative thinking and open-mindedness but who were, at the same time, cognisant of the limitations these managerial styles may hold. This sub-theme links to sub-theme A4.5 (role of management/acceleration).

> "*[Management] has to allow you to do what you want to do – within limits, of course*" (R01).

The notion of freedom extends beyond simply "*academic freedom*" (R12), or "*complete freedom to do what I want*" (R04). Work climates should also allow for "*the freedom to follow*

up on a neutral result" (R03), or to "*let the problem take me where it wanted, rather where somebody else wants me to go with it*" (R04). Other responses highlighted the importance of providing "*the opportunity to do unconstrained research*" (R03), the "*freedom to explore*" (R23) or managerial "*free reign*" (R14).

It was also noted that free work climates may produce a cycle of continuous improvement. This linked closely to the perspective of seeing "*the bigger picture that [one] is embedded in*" (R29). Moreover, to create a free work climate, "*resources [and] time… and more responsibility*" (R19) were noted as essential. However, respondents noted that managerial structures do need to manage freedom to stimulate creativity and innovation. This point was related to younger academics.

> *"[Y]oung people typically make all the big breakthroughs. It's very rare that you get someone at my age who makes a big breakthrough, the young people, people who are in their 20s and 30s … typically make all the breakthroughs because they have no fear. They don't know enough to be told that what they're doing is crazy. And even if they are, they don't listen* (R03).

Respondents noted that over-emphasis on financial duties, such as grant proposals and lack of basic funding could have detrimental implications such as "*demotivation*" (R01). Financial freedom is considered linked to greater research freedoms. "*Freedom is more difficult now because of this tremendous financial pressure on people"* (R19).

Based on these findings, it is proposed that freedom is a positive driver of BRP. Working climates that are perceived as fee of constraints, that encourage exploration, are well-structured and allow sufficient access to resources may be more likely to be conducive to producing breakthrough research outputs.

4.4.2.2.2 Sub-Theme B2.2: Incentive

Several respondents noted the importance of reward structures and incentives that can be used to foster innovative working climates. This sub-theme links to motivation. Both intrinsic and extrinsic incentives were cited as important contributors to innovation.

"*Reward the researchers as best as you can, not necessarily with money but with kudos. Recognition. That's what we want. Scientists, academics have a personality that is competitive, and our intellect is always being challenged and criticised throughout our whole lives and what we want is to hear someone saying, 'you did good'"* (R01).

In general terms, respondents agreed that intrinsic incentives and rewards are more effective powerful extrinsic incentives and rewards. *"I don't want money. I'm not interested in that*" (R01). Intrinsic rewards such as recognition and acknowledgement of achievement were highly cited as primary innovation drivers. Environments that encourage innovation by providing such intrinsic motivators are conducive to generating breakthroughs.

"*All the faculty members are very focused on doing research and getting results so you're in an environment in which this is valued*" (R08).

Cultivating an environment in which innovation is valued builds an innovative culture, which can become ingrained within a laboratory or institution, if managed correctly.

"*There's an excitement that you can build, and it will pull out innovation. We have innovation clause that searches for and asks for everyone to be innovative in everything they do and then rewards them accordingly. It's very helpful but I think it helps to have a reward system of some sort, even a small reward*" (R09).

Based on these findings, it is proposed that incentives are a positive driver of BRP. Working climates that encourage innovation through reward, recognition and achievement may be more conducive to producing breakthrough research outputs.

4.4.2.2.3 Sub-Theme 23.3: Collaboration

Collaboration refers to cross-disciplinary collaboration, communication, cooperation and the sharing of data, knowledge and information. Environments that stimulate cross-disciplinary collaboration are expected to cultivate high levels of innovation through the interaction of diverse knowledge inputs. Respondents cited the importance of "*external problems ... a connection with the outside world*" (R4) and the interactions of "*people from different labs and consequently with different backgrounds*" (R07), which helps researchers "*look at it from a*

different perspective" (R07). This sub-theme links to several others, including sub-themes A1.3 (openness), A4.1 (open orientation), B1.1 (education and training) and B1.3 (cross-pollination). There was, however, also an indication that collaboration needs to be carefully managed, based on individual differences. Respondents spoke at length of the dangers of overly open collaboration.

> "*[You are] wary of this generous atmosphere, you're not always aware of your … if some of your idea might be stolen by some of your colleagues … [I am] reluctant to exchange my ideas with my colleagues in … that they might somehow steal from me*" (R05).

The potentially detrimental effects of "*jealousy and discrimination, sometimes open contempt*" (R13) were also mentioned.

Conversely, most respondents did agree that cross-collaboration, particularly with researchers from different areas of expertise, was a fundamental aspect of fostering an innovative working climate.

> "*If the work had not been fun and the people I worked with not a pleasure to work with, I would have shifted to some other area*" (R07).

This sub-theme also linked closely to satisfaction (sub-theme A2.2) in the "*fun*" (R14) aspect of collaboration. This can be attained by *"[creating] good camaraderie*" (R14), to keep "*people … inspired*" (R14) by their colleagues. The careful balance which must be attained regarding individual differences and fostering collaboration is well summarised in the following quotes:

> "*One has to be working with colleagues with whom one can share one's thinking, who can be continually critiquing in a friendly way, what one is doing, who are helpful, who are not constructive or too competitive. In some groups people are internally competitive with one another, in some groups they're not interested in helping one another. In some groups, there may actually be significant tensions between people, and in some groups, they meet only rarely with the person who was reportedly mentoring them. So those are some of the aspects of the climate which ultimately will determine how successful they are because - at least in my field of research–people cannot work in a vacuum"* (R15).

"*And in terms of motivation, its often heavily influenced by one's environment, because if you're in an environment in which other people are doing interesting things and other people doing 'off the beaten track' stuff and other people are taking chances and are ambitious and hard-working; just being in that environment – even if it doesn't provide any direct help −is a tremendous benefit for motivation; … being in the same place as other students and teachers and colleagues is a tremendous support to the motivation [that] one might have to take risks and to do things unusual*" (R22).

Based on these findings, it is proposed that collaboration is a positive driver of BRP. Working climates that encourage cross-disciplinary sharing of knowledge and information and that foster values associated with sharing and openness may be more conducive to producing breakthrough research outputs.

4.4.2.2.4 Sub-Theme B2.4: Managerial Support

Many respondents had previously worked in management positions. These respondents therefore had numerous suggestions for the role of management in stimulating scientific curiosity and innovation that lead to breakthroughs.

"*The institutions actually create environments that are more or less supportive of trying to do risky research*" (R26).

Respondents agreed that the primary a role of management is to provide "*adequate resources*" (R23), particularly "*the tools and capacities that you need at hand*" (R22) and "*community resources*" such as "*the production of, and curation of, and free availability of databases and data sets and knowledge bases, with the idea that whoever wants to use them can use them*" (R16). Financial freedom (sub-theme B3.1) and collaboration (sub-theme B2.3) linked closely to managerial support. Standard management support in the form of "*technical assistance*" (R10), "*respect*" (R21), "*trust*" (R14) and "*guiding, rather than criticising … [giving] people courage*" (R21) were also repeatedly mentioned. The combination of these were considered crucial amongst respondents to "*create an atmosphere in a laboratory which is conducive to both scientific and personal growth*" (R25). The issues of work/life balance were also addressed, with respondents stressing again the importance of freedom, "*because I think*

unhappy people are not going to do the best science" (R25). This may be supported by "*creating an environment that supports the full human activity"* (R25). Based on these findings, it is proposed that managerial support is a positive driver of BRP. Working climates that offer managerial support in the form of semi-fluid working structures, access to resources and mentorship are more likely to be conducive to producing breakthrough research outputs.

4.4.2.3 Proposition B3: Availability of Resources, financial freedom and a reduction of bureaucracy are positive drivers of BRP

Resource availability refers primarily to the availability and ease of access to financial resources. It also includes the availability and access to lab equipment and staff as well as the availability and free flow of knowledge, data and information. Financial freedom, a reduction in unnecessary bureaucracy and securing diverse sources of funding were all cited as important precursors to BRP. These are summarised, in Table 20 below and discussed thereafter.

Table 20: Resource Availability (sub-themes)

Number	Theme Title	Key concepts	Respondents
1	**Financial freedom**	Funding, freedom, finance, resources, time, effort, creativity, boundaries	R03, R04, R50, R09, R15, R25, R26, R27
2	**Reducing Bureaucracy**	Red-tape, restrictions, time, freedom, politics, ideologies	R08, R09 R14, R15, R18, R22
3	**Diverse source of funds**	Private sources, restructuring funding agencies, funding flexibility, incentives	R02, R03, R16, R17, R21, R26, R27,

4.4.2.3.1 Sub-Theme B3.1: Financial Freedom

Financial freedom refers to the freedom to conduct research without being financially constrained.

> "*Science needs some area to be totally creative and not bounded by expectation. It encourages independent thought and creates activity of knowledge generation and blue-skies as well as more standard kind of high-quality research*" (R09).

While financial freedom is essential, there does need to be safety mechanisms in place to restrict overly generous research funding, "a*s long as they're not really stupid and somebody's crazy dream that theoretically could possibly be true*" (R26). Several respondents suggested the use of 'trial periods', for both established and non-established researchers.

> "[To do] *whatever they want for five or six years. Whatever it is they want to do. And then after five or six years, now you can start to judge whether these people have been good or bad or different and then you can decide whether you're going to continue to fund them or not*" (R03).

Some respondents noted the importance of encouraging young researchers by providing trial funding in the early parts of their research careers with a "*first grant which allows them enough money to pursue what they want to do. A grant to get going*" (R25). Others felt that trial funding and trial periods to allow for would be better suited to more established researchers with proven track records.

> "*Look at a person's record over the last three to five years in terms of their productivity and on the basis of that, giving them money to run their labs rather than looking at what they propose to do, which has limited utility in terms of its ability to predict about what they about to discover. In other words, giving money to the person rather than to the project*" (R15).

The difficulty in differentiating between potentially useful and useless radical research was an area of contention.

> "*Define good researchers and give them the money they need, and the question is how do you find good researchers?"* (R04).

> "*That's tough, because you just don't know what to fund there but that's where the innovation comes from"* (R27).

A potential solution to this dilemma was suggested.

"[To] try identify a relatively small number of individuals who they regard as particularly promising and then simply give them a certain amount of money for a limited amount of time and say go off and do whatever you want" (R05).

Financial freedom was also found to be linked to sub-themes A2.5 (extrinsic motivation) and B2.2. (incentive), albeit weakly. Based on these findings, it is proposed that financial freedom is a positive driver of BRP. Of the resources required to stimulate breakthrough research productivity, those that are financial and come in the form of research grants and funding are considered vital to producing radically innovative research outputs. Furthermore, time, as a resource is also essential to the production of breakthrough outputs. The combination of financial resources and time may help to stimulate creativity and enhance the likelihood of producing radically innovative outputs.

4.4.2.3.2 Sub-Theme B3.2. Reducing Bureaucracy

Financial freedom and easy access to resources is considered important to BRP. In most cases however, these are constrained by significant bureaucratic obstacles, also referred to as 'red tape'. Reducing rep tape and restrictions may enhance BRP, rather than inhibiting it.

"*It costs us a lot of time. It wears people out* (R14).

"*Sometimes just having $5 000 or $10 000 with no strings attached and a short proposal can be worth many times that amount than if it has to be justified in detail and go through a peer review process and with a demonstration of why it's going to work or help mankind. And so, I commend institutions that have some system of giving small amounts of money to interesting things without too much justification*" (R22).

The drawbacks of bureaucratic restrictions relate primarily to the excess of red-tape, rules and regulations and "*a tremendous amount of paperwork involved … a lot of oversight*" (R14) that hinders efficient grant proposal and subsequent funding. Time is a resource that is commonly lost in this exchange.

"*A lot of time gets wasted…. So, I would say you know a climate in which there's more money available, so you don't have to spend so much time trying to raise money would be helpful*" (R08).

Respondents suggested "*scaling back*" (R14) bureaucratic procedures to get the best out of researchers. Some respondents were scathing in their critique of bureaucratic funding procedures.

"*It's rarely been the case that I undertook the research pursued that I proposed to do by the time the funding comes back, one's thinking has moved on and moved in new directions and so this is really a very counter-productive way of funding innovative science, discovery science"* (R15).

"*That's a difficult thing all the time because donors are often reluctant to trust researchers to really be doing what it is that [the] researcher sought out to do …. That's a delicate balance and requires some faith and time investment by the sources of funding as well as faith and time use by researcher himself…. So, the innovator finds itself in strong conflict with the bureaucracy in which they're embedded which generally stops the person from being an innovator that's very effective*" (R18).

While these quotes may show the significance of the problem of bureaucracy, some respondents did also note its need.

"*On the other hand, from the innovator's side of things you get people who think of lots of new ideas but are not capable of putting them into a structure that carries them forward. They have a lot of good ideas but aren't willing to put the time and energy into creating a broad guideline and structure that will carry the idea forward and make it bigger and will be used by more people. So, both the innovator and the person strongly adapted to a bureaucracy are stuck in their lineage. It's hard for them to bridge between the two. We spend a lot of time trying to build those bridges between the two, but we do meet lots of resistance*" (R18).

An additional form of bureaucracy was mentioned several times in the form of political interference. This refers to institutional or faculty-wide ideologies and principles that are not

conducive to radical innovation and breakthroughs. But, the political influence on scientific research can also be taken as a positive.

> "*Political influence may help to focus and structure discovery science on important societal problems and that this renewed focus and structure may help direct research grants in the right direction, rather than allowing either too much bureaucracy and red-tape, or at the other extreme – too much free reign*" (R09).

> "*The biggest challenge right now is that politics around the world is intruding on that part of science which is engaged in true discovery. There's a good reason for that; science has exploded in its capability and has fostered an interest in helping science focus itself on those areas of research that is likely to have more societal benefit*" (R09).

Recent examples relating to potential threats of political interference in discovery science were also noted. Several respondents cited the current USA political administration's denial of climate change as an example.

> "*It's very bad if dogmatic rules come into play. For example, our current administration is not too keen on the assumption that humans have caused climate change. When ideologies come in, we see things set back*" (R09).

Based on these findings, it is proposed that the reduction of bureaucracy is a positive driver of BRP. The mitigation of 'red-tape' restrictions and a removal of political influences and narrowly-defined ideologies may decrease barriers to creativity and enhance academic freedoms, significantly enhancing the probability of producing breakthroughs.

4.4.2.3.3 Sub-Theme B3.3: Diverse Sources of Funds

Many respondents cited the importance of funding flexibility, and the use of diverse sources of funds to improve research productivity and generate innovation. Respondents often reported the reluctance and "*conservative*" (R26) nature of grant agencies to fund new projects, especially in the case of research that is considered outside of the norm.

> "*I think there's great virtue in a diversity of research funding sources"* (R21).

"*We need to do is to make sure that the people who are judging grants are much more open minded in terms of what they're prepared to consider. I mean one of the problems that happens in the US all the time is that the study sections tend to be unbelievably conservative; they often demand way too much from grant recipients and what the grant recipients are proposing*" (R03).

This is a problem that does not seem to differ by geographical location, education, upbringing, training, experience or journal publication perception (sub-theme A4.6). Almost all respondents agreed that a higher level of leniency towards grant proposals and funding would stimulate more innovative research and the occurrence of breakthroughs.

"*I think the funding agencies get a reputation for not in many cases not supporting innovative research really"* (R16).

Furthermore, grant and funding agencies were often described as "*theoretically disinterested*" and have become "*more and more risk averse*" (R27). Less risky projects, meticulously built on previous studies, are more likely to be funded. This may therefore lead to a preference of grant and funding agencies to fund incremental innovation, rather than radical innovations.

"*The trouble with that is that then that that research is never really innovative. It moves the needle 1 micron forward at a time whereas most truly innovative things are right-angled turns and the funding agencies – particularly in times when funding is tight – will naturally fund those things that are going to be more predictably successful"* (R27).

However, it was also noted that funding agencies may be reluctant because of the high level of risk associated with radically innovative research, which many claimed is a valid concern.

"*Sometimes funding agencies are a bit reluctant because they're taking a risk that they put the money into something which in the end maybe doesn't work as well as it was advertised in the proposal*" (R17).

"[T]here's nothing wrong with that. That research could be really valuable, it could be the one next step that revolutionizes the field, but most truly innovative things are right-

angled turns and funding agencies quite appropriately are very reluctant to fund anything that's out of the mainstream and the problem with that is that you don't get true innovation. Of course, it's tough to know what out-of-the-mainstream is going to be successful, so it's a much more riskier area to fund which the reason it tends not to be funded very much" (R27).

One respondent (R26), currently at the helm of a large funding agency, described a new methodology recently implemented to foster greater levels of funding for research projects that are risky, or radically innovative.

"*We have gone out of our way to try to foster an environment where we fund riskier projects*" (R26).

This respondent reported a success in new funding techniques, using incentive programmes, which award researchers who can continually prove their aptitude for producing innovative research and potential breakthroughs.

"*We have a lot of short-term awards where the amount of preliminary research needed is small to none. So, you're trying to essentially give awards to what are thought to be really new ideas*" (R26).

Another reward, referred to the 'outstanding investigator' award, was described as "*very different from the usual application".*

"What have you done in the recent past – that's particularly noteworthy and what has your contribution been to that area or those areas? There are no specific aims to the research proposal, it's just what would you like to do and how would you like to go about doing it. The idea is to provide resources with virtually complete flexibility for the investigator" (R26).

Another respondent also described a new method of funding, in which an association of "*about 25 investigators from different institutions*" collaborate annually with the intention of idea generation.

> "*[O]ne or two ideas of important or unanswered problem in particular areas of research. These questions that are debated among a group of 25 and [we] usually come out with a few questions and then each year we publish about a dozen of them. Anybody who wants to, can essentially submit an application that hopefully tries to address one of the questions in a potentially meaningful way. So that's another way in which we have tried to get people to be risky because we've tried to select for questions for which there aren't answers but for which we think there might be technology that could help to provide answers"* (R26).

Another important source of funding that seemed popular amongst respondents was that of private funders.

> "*We've found funders who were independent of the outcomes. Because once you have a funder who depends on the outcome, your research is shot, and you'll only find what they want you to find. And so, we find that the companies that were prepared to allow us to do what we wanted to do were better*" (R02).

The combination of diverse fund sources may allow researchers to "*piggy back*" (R19) their way into pursuing their own research interests. The combination of "*non-legitimate or no-peer-reviewed methods"* (R19), along with private funding and typical grant applications may provide a diverse enough source of funding to allow researchers to pursue innovation. Despite the fact that almost all qualitative respondents agreed that research funding tends to be scarce, no mention of crowdfunding or other new methods of fund aggregation were made. Based on these findings, it is proposed that a diverse source of funds is a positive driver of BRP. The flexible allowance of research fund sourcing from private and public sources may enhance the probability of potentially breakthrough research being funded and therefore, carried out. The links and associations between themes that make up Proposition B, related to the external drivers of BRP, are depicted in Figure 16, below. The associations and links between both internal and external drivers of BRP are depicted in Figure 17. The highlighted section of Figure 16 shows associations which tend to converge around open orientation, education and experience, collaboration and cross-pollination. It is stressed that all relationships depicted in figures 16 and 17 are positive, given that these diagrams represent positive drivers of BRP. These are discussed further in Chapter 6. A summary of the qualitative themes is provided in Table 21.

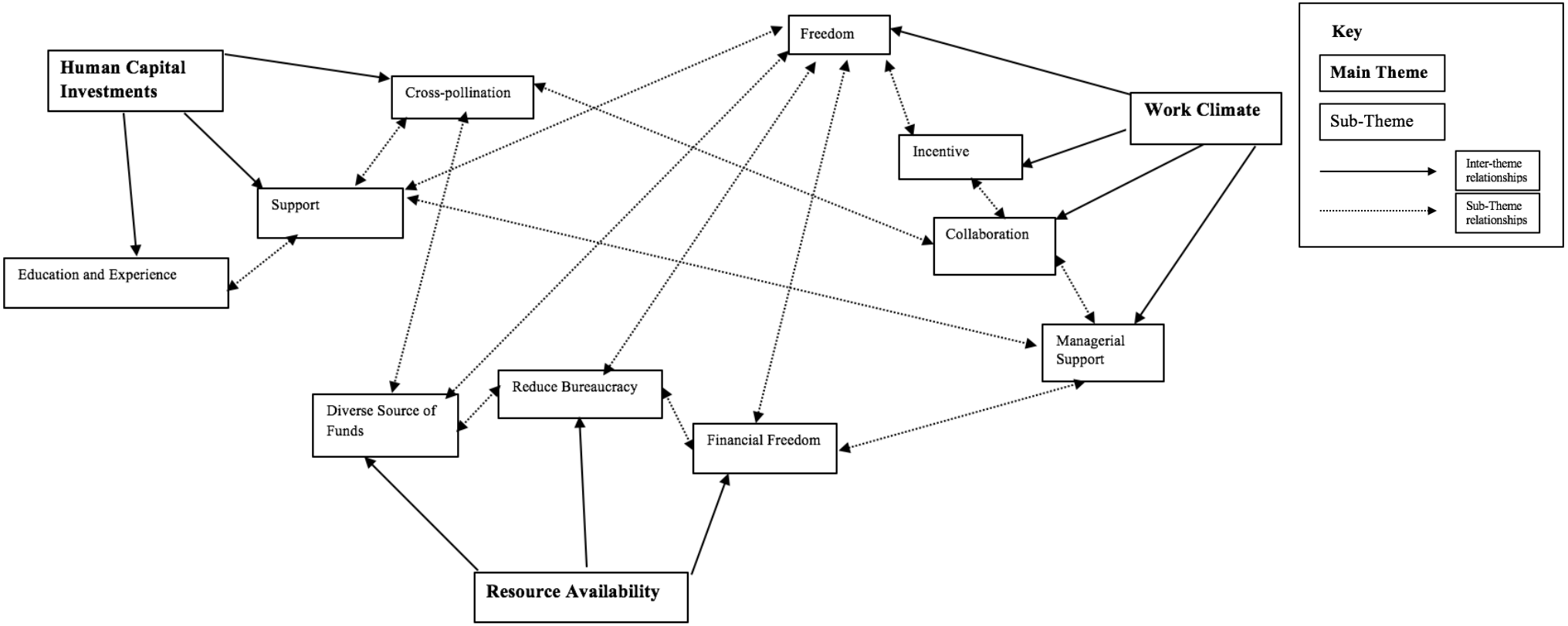


Figure 16: External Drivers of BRP

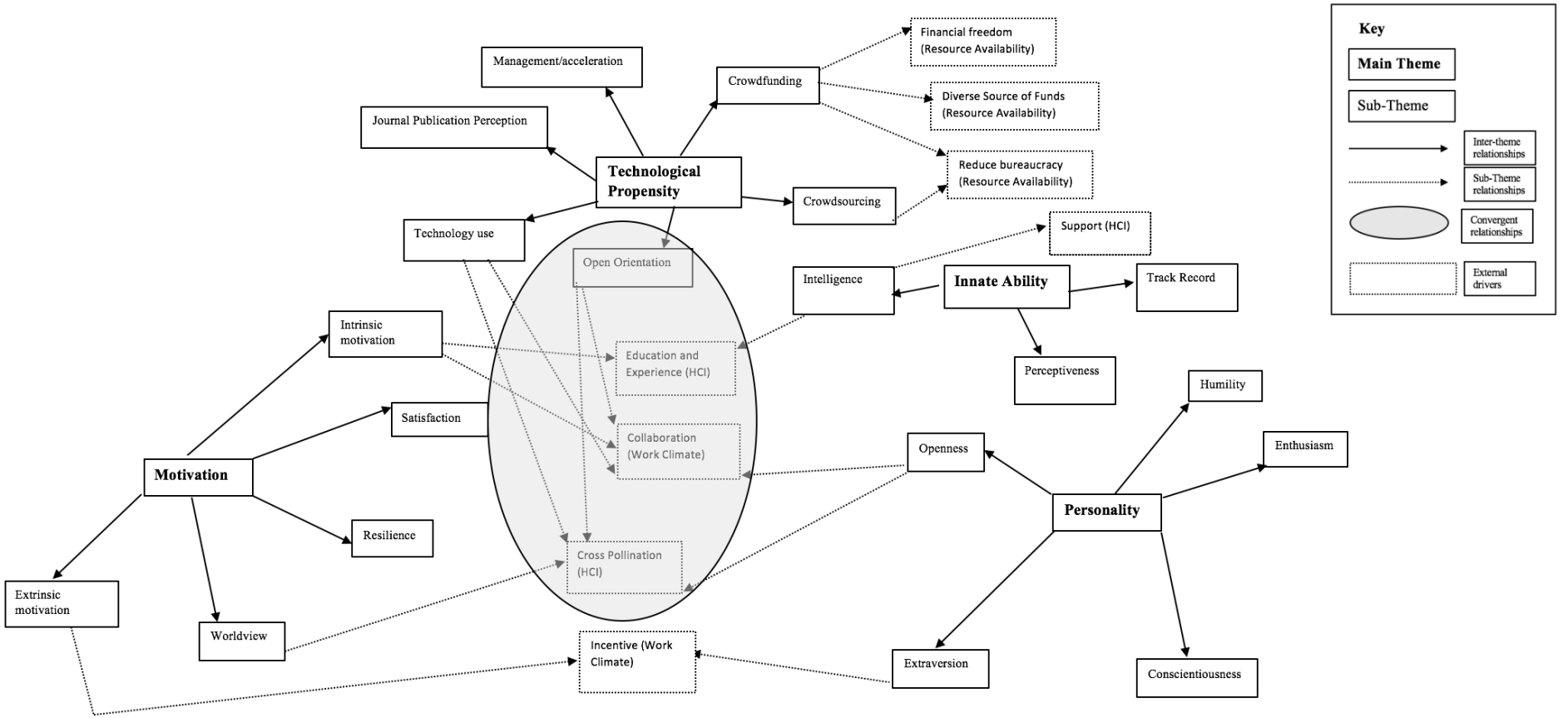


Figure 17: Primary associations between internal and external drivers of BRP.

Table 21: Summary of qualitative themes

Breakthrough Research Productivity (BRP)	Theme Code/Proposition	Themes	Sub-Themes	Key concepts	Direction of relationship	Linkages/Associations
Internal Drivers	A				Positive	
	A1	Personality			Positive	
	A1.1		Humility	• Humbleness • Humility • Collaboration	Positive	A1.3 (Openness) A1.5 (Extraversion)
	A1.2		Enthusiasm	• Energy • Thirst/hunger/desire • Curiosity • Passion (excitement)	Positive	A2.1 (Intrinsic Motivation) A2.3 (Satisfaction)
	A1.3		Openness	• Scientific gregariousness • Curiosity • Creativity • Independent thought and rejection of conventional wisdom • Imagination • Link to HCI (education and experience) • Intelligence/ability	Positive	A4.1 (Open orientation) A1.5 (Enthusiasm) B1.3 (Cross-Pollination) B2.3 (Collaboration) A3.1 (Intelligence)
	A1.4		Conscientiousness	• Independence and independent thought • Perseverance and persistence • Focus and drive (motivation)	Positive	A2.4 (Resilience) B2.2. (Incentive)

	A1.5		Extraversion	• Collaboration (sharing data, knowledge and information) • Communication and cooperation	Positive	A1.3 (Openness) A4.1 (Open Orientation) B1.3 (Cross-Pollination) B2.3 (Collaboration)
	A2	Motivation				
	A2.1		Intrinsic Motivation	• Truth • Desire • Creativity • Independence • Hunger/thirst/desire for knowledge and truth • Link to satisfaction (excitement)	Positive	A1.2 (Enthusiasm) A2.2. (Satisfaction) B1.1. (Education and experience) B1.2. (Support)
	A2.2		Satisfaction	• Fun • Love	Positive	A2.1. (Intrinsic motivation)
	A2.3		Resilience	• Willpower and determination • Bravery • Optimism (belief)	Positive	A1.4 (Conscientiousness) A3.2. (Track record)
	A2.4		Worldview	• Humanistic/altruistic • Helping society • National pride	Positive	A3.3. (perceptiveness) A1.1. (Humility) A4.4. (Technology Use) B1.3. (Cross-pollination)
	A2.5		Extrinsic Motivation	• Reputation • Ambition for power, glory or money	Positive	A4.6 (Journal Publication Perception) B2.2 (Incentive)
	A3	Innate Ability				
	A3.1		Intelligence	• Intellectual	Positive	A3.3 (Perceptiveness)

						B1.1. (Education and experience) B1.2 (Support) A1.4 (Conscientiousness)
	A3.2		Track Record	• Accomplishments (prior achievements) • Productivity	Positive	B1.1 (Education and experience) A1.4 (Conscientiousness)
	A3.3		Perceptiveness	• Ability to see the bigger picture • Competence • Experience	Positive	A3.1 (Intelligence) B1.1. (Education and experience)
	A4	Technological Propensity				
	A4.1		Open orientation	• Cross-pollination, collaboration, communication • Openness • Sharing data, knowledge and information • User-innovation • Big Data • Journal publication perception (anti-publication vs. pro-publication)	Positive	A1.3 (Openness) A2.5 (Worldview) A1.5 (Extraversion) B1.3 (Cross-pollination) B2.3 (Collaboration)
	A4.2		Crowdsourcing	• Open innovation • Incentives • Expert knowledge vs. common knowledge • Importance of speed (immediacy) • Communication and coordination	Positive	A4.3. (crowdfunding) A1.3 (openness) A4.1. (open orientation) A4.4 (technology use) A4.5 (management/acceleration)

				• New technologies (Internal and social media) • Real-time solutions • Open access journals		A4.6 (Journal Publication Perception) B3.4 (Bureaucracy)
	A4.3		Crowdfunding	• Resources • Speed/immediacy • Governmental funding • Financial freedom • Diverse source of funds • Links to climate and motivation	Positive	A4.2. (crowdsourcing propensity) A1.3 (openness) A4.1. (open orientation) A4.4 (technology use) A4.5 (management/acceleration) A4.6 (Journal Publication Perception) B3.4 (Bureaucracy) B3.1 (Financial freedom) B3.3 (Diverse source of funds)
	A4.4		Technology Use	• Economies of scale • New technologies (Internet and social media) • Speed and scale of dissemination of information and data • New technologies (Internet, social media, Big Data, Artificial Intelligence, surveillance systems) • Increased efficiency • interconnectivity	Positive	A1.3 (Openness) A1.5 (Extraversion) A2.5 (Worldview) A4.1 (Open orientation) A4.2. crowdsourcing propensity) A4.3 (Crowdfunding propensity) A4.5 (management/acceleration)

						A4.6 (Journal publication perception) B1.3 (cross-pollination) B1.3 (collaboration)
	A4.5		Management of research/acceleration	• Managerial support • Freedom and creativity • Increasing probability (Economies of scale) • Organisational objectives vs. curiosity • Links to work climate, motivation and openness • Knowledge silos • Possible to attain ARI vs. impossible to attain ARI	Positive	A1.3 (Openness) A1.5 (Extraversion) A2.5 (Worldview) A4.1 (Open orientation) A4.2. crowdsourcing propensity) A4.3 (Crowdfunding propensity) A4.4 (Technology use) A4.6 (Journal publication perception) B1.3 (cross-pollination) B1.3 (collaboration)
	A4.6		Journal Publication Perception	Pro-Publication vs. Anti-Publication (See Table 17)	Neutral	A1.3 (Openness) A1.5 (Extraversion) A2.5 (Worldview) A4.1 (Open orientation) A4.2. crowdsourcing propensity) A4.3 (Crowdfunding propensity) A4.5 (management/acceleration) B1.3 (cross-pollination)

						B1.3 (collaboration)
External Drivers	B					
	B1	Human Capital Investments (HCI)				
	B1.1		Education and Experience	• "Know the basics" • Early environmental support • Background (nationality)	Positive	A3.1 (Intelligence) A3.2 (Track record) A3.3 (Perceptiveness) B1.2 (Support) B1.3 (Cross-pollination)
	B1.2		Support	• Early environmental support • Stimulating independent thought • Mentorship and guidance	Positive	B1.1 (Education and experience) B2.4 (Managerial support)
	B1.3		Cross-pollination	• Different areas of training (diverse HCI) • Creative thinking • Perspective • Rejection of conventional wisdom • Collaboration	Positive	A1.3 (openness) A1.5 (extraversion) A4.1 (Open orientation) B2.3 (Collaboration)
	B2	Work Climate				
	B2.1		Freedom	• Financial freedom • Exploration and opportunity • Continuous improvement • Perspective • Resources (time) • Incentive and motivation • Young vs. experienced academics	Positive	A1.3 (openness) A4.1 (open orientation) A4.5 (management/acceleration) A4.6 (journal publication perception) B1.2 (support) B2.4 (managerial support)

						B3.1 (financial freedom) B3.2 (bureaucracy)
	B2.2		Incentive	• Link to motivation: rewards, recognition and acknowledgement	Positive	A2.6 (extrinsic motivation) A4.5 (management/acceleration) B2.4 (managerial support)
	B2.3		Collaboration	• Cross-pollination/cross-disciplinary collaboration, communication, cooperation • Sharing information, data and knowledge • Inspiration through comradery and competition	Positive	A1.3 (openness) A1.5 (extraversion) A2.5 (worldview) A4.1 (open orientation) A4.5 (management/acceleration) B1.3 (Cross-pollination)
	B2.4		Managerial Support	• Resources (time) • Freedom • Work-life balance • Trust and respect	Positive	B3.1 (financial freedom) B3.2 (bureaucracy) B2.2 (incentive) B2.1 (freedom) B1.2 (support) A2.6 (extrinsic motivation)
	B3	Resources				
	B3.1		Financial freedom	• Freedom • Creativity • Careful balance of management • Young vs. established academics • Links to motivation and climate	Positive	A2.1 (intrinsic motivation) A2.6 (extrinsic motivation) B2.1 (freedom) B2.4 (managerial support)
	B3.2		Reduce Bureaucracy	• Red tape/regulation	Positive	A2.4 (resilience)

				• Political and ideological interference		B2.1 (freedom) B2.4 (managerial support) B3.3 (diverse source of funds)
	B3.3		Diverse source of funds	• Flexibility, openness and leniency • Need to reduce conservatism • Need to be less risk-averse • Incentives, incentive programs and rewards • Collaboration • Private funders • "Non-legitimate" sources		A1.3 (openness) A2.3 (satisfaction) A4.1 (open orientation) A4.2 (crowdfunding propensity) B1.3 (cross-pollination) B2.1 (freedom) B3.1 (financial freedom) B3.2 (bureaucracy)

4.5. CONTRAST BETWEEN THEORETICAL MODEL AND QUALITATIVE FINDINGS

The results of the qualitative analysis were contrasted with the theoretical model which was derived from the literature. A broad overview of the findings of the qualitative study are shown in Figure 18 as illustrated below.

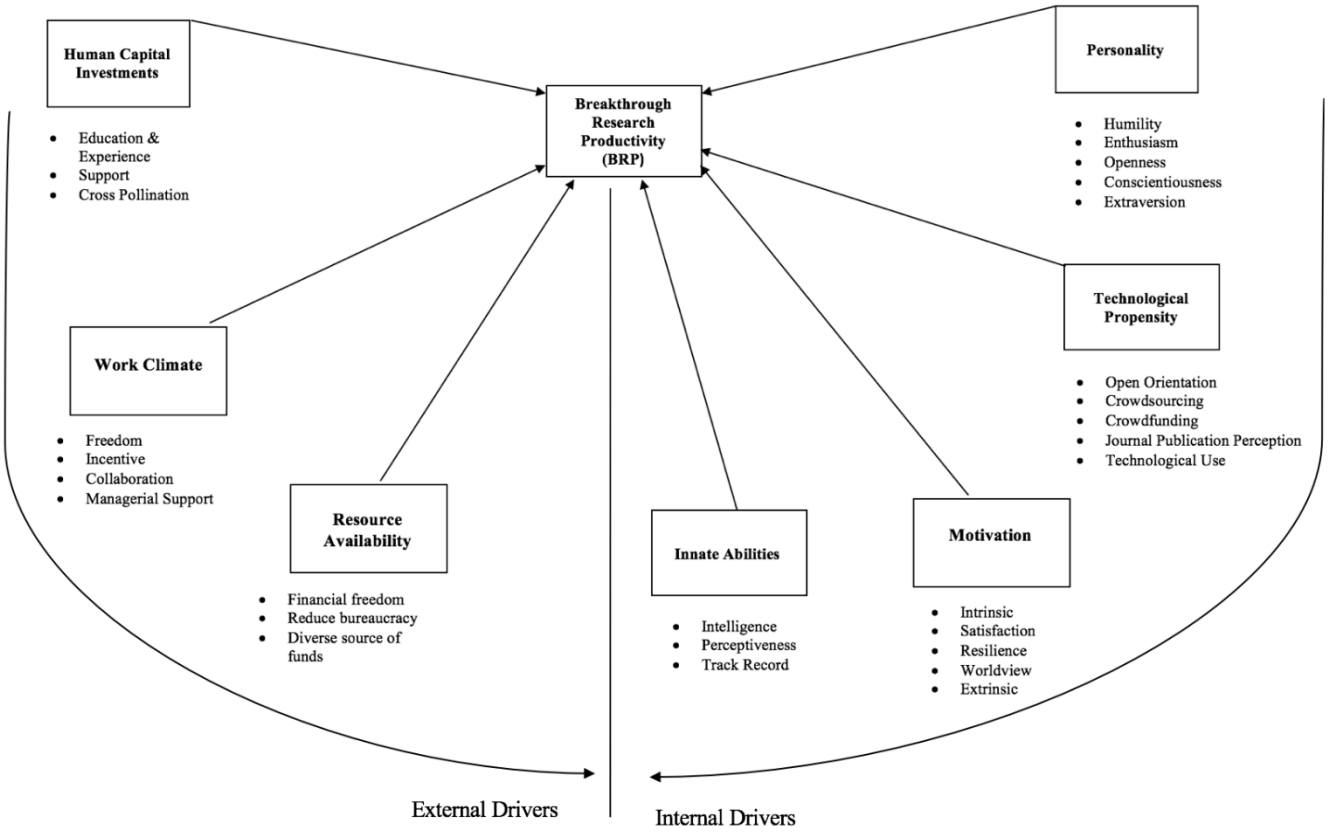


Figure 18 Model of qualitative findings: Determinants of BRP

Although there were some differences, the model derived from the qualitative analysis mostly matched that of the model derived from the literature, likely owing to the proximity of the interview schedule to the literature. Most notable is the differentiation between internal and external drivers of BRP. It is suggested that these two categories impact BRP in different ways. Internal drivers, including personality, motivation, innate ability and technological propensity represent drivers or influences that are inherent to the individual and may therefore differ from person to person. External drivers include human capital investments, work climate and

resource availability which are distal to the individual and may impact performance. These may therefore differ serendipitously, based on geographical location, upbringing, nationality, gender, age, social environment and experience.

The differences between the model derived from the literature, and the model built from the qualitative analysis are now discussed. In terms of human capital investments, the most striking difference was the importance of the diversity of education and experience, referred to as HCI diversity. HCI diversity refers to the influence of cross-pollination of knowledge from areas or fields outside of one's primary focus. The assessment of personality revealed a high regard for humility, often referred to as "being humble", which does not match any of the constructs of the FFM model of personality. Enthusiasm was also mentioned frequently but this may potentially form a component of openness to experience or extraversion. Conscientiousness related to perseverance and persistence but was also strongly related to independence, or independent thought. Respondents noted the stark differences between intrinsic and extrinsic motivations, but also noted that both may potentially contribute to BRP. In terms of Schwartz's (1992) model of higher order values, self-transcendence was revealed in the form of worldview and openness to change. A form of self-direction was revealed in resilience and satisfaction. Satisfaction also seemed linked to achievement. King and Anderson (2002) suggest that cognitive ability is an important precursor to innovative output, and while this was not intentionally measured, respondents did reveal that innate ability (consisting of sub-themes intelligence, perceptiveness and track record) were important contributors to BRP. In terms of work climate, respondents generally agreed on the importance of freedom and collaboration, which both fall under the OSM-type climate models (Patterson, et al., 2005). The mention of incentives, managerial support and availability of resources was also made in reference to climate. In terms of technological Propensity, qualitative results produced mostly similar constructs, with the addition of journal publication perception, which gave a generalised assessment of respondents' view towards the academic publishing system. A model was derived from qualitative analysis. From this model, propositions were derived. These derivations are depicted in Figure 19, below.

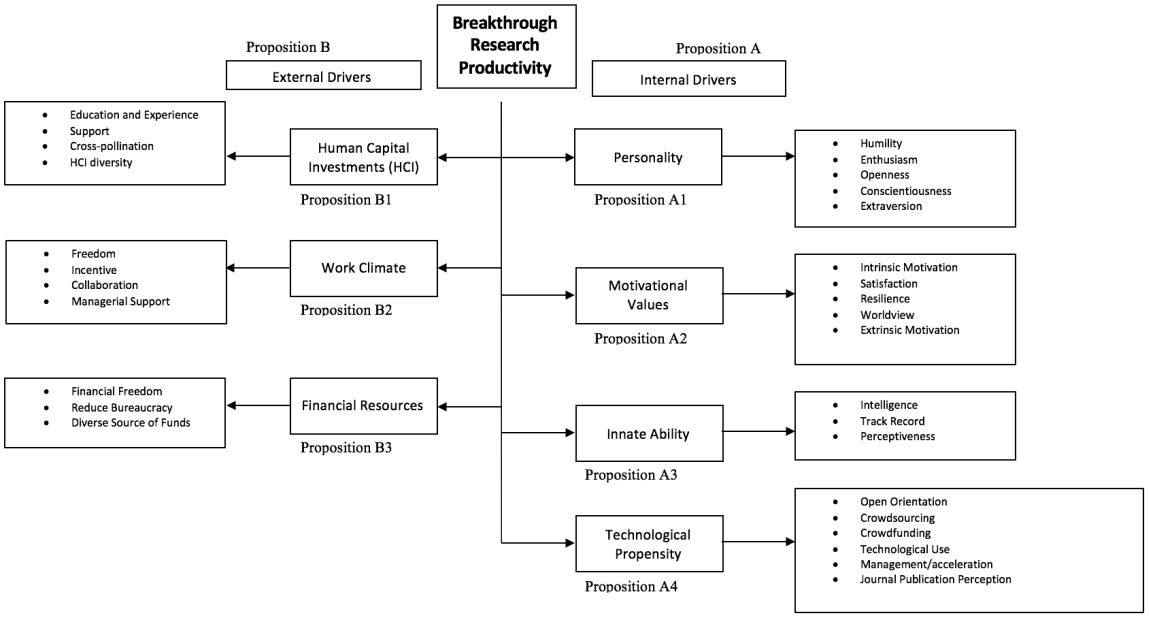


Figure 19: Derivation of Propositions

4.6 CHAPTER CONCLUSION

In this chapter, the results of the grounded qualitative analysis were reported and interpreted. This chapter extends the work of the literature review and methodology chapters, where theory and previous findings are reviewed, and an appropriate methodology is derived for this study. In this chapter, an inductive qualitative analysis followed for an understanding of relationships that are independent of the constraints of pre-existing theory, namely of relationships discovered in this specific context. It is stressed that this chapter serves only to report the findings of the qualitative analysis. Chapter 6 includes a detailed analysis of these results, in relation to literature, and in relation to the findings of the quantitative analyses. Using thematic content analysis, themes were analysed and categorised under themes and sub-themes. Propositions relating to the determinants of BRP were derived and discussed. It was noted that the determinants of BRP, as per the results of the qualitative analysis could be broadly grouped into two categories, including external and internal influences. These broad categories formed the foundation for the derivation of further sub-propositions. At this point, the analysis is extended further, into the reporting of the quantitative results of the study. This chapter builds on the previous chapters, as the results of further analysis add different perspectives of the phenomena under investigation. The quantitative results are reported in the chapter that follows. Chapter 7, which contains a discussion of the results discussed in Chapters 4 and 5

follows and recommendations and conclusions are provided in Chapter 7. The results of the quantitative research are now reported.

CHAPTER 5
QUANTITATIVE ANALYSIS

5.1 INTRODUCTION

The results of the statistical testing of the hypotheses is reported in this chapter. Theory that relates technological propensity to research productivity was tested empirically. Two quantitative samples were analysed. These include i) a sample of South African academic researchers (n=457) and ii) a sample of 'crowd-workers' or MTurk users (n = 595). This chapter is reported in two sections, corresponding to each of these samples. Section A reports on the academic researcher sample. Section B reports on the crowd-worker sample. In each section, the univariate, bivariate and multivariate results are reported. The results of exploratory factor analyses are also reported. In the sub-sections entitled 'univariate results', the measures, location, central tendency and statistical dispersion of the major variables under study are reported. In the sub-sections entitled 'bivariate results', bivariate characteristics of the data that have implications for the interpretation of results are reported. In the sub-sections entitled 'multivariate analysis' the multivariate results are reported, as are the tests of the assumptions of the statistical methods. These include multiple hierarchical regressions, mediations and moderations. The reporting of results is structured according to the hypotheses. Results are discussed further in Chapter 6. The reporting of results pertaining to the South African academic researcher sample now follows.

5.2 SECTION A: ACADEMIC RESEARCHER SAMPLE ANALYSIS

The results of the analysis of the South African academic researcher sample are now reviewed. This sample comprised of 457 academic researchers from nine different South African universities. Univariate, bivariate and multivariate results are reported, respectively.

5.2.1 Univariate Results: Measures, Location, Central Tendency and Statistical Dispersion

A comprehensive univariate analysis was performed. The data were checked for missing variables (see Chapter 3) or capturing mistakes. Measures of location, central tendency and statistical dispersion were applied, and are reported for each of the tested variables. The means, medians, mode values, standard deviations (std. deviations) and variances were derived, and these are reported in the following sections. The univariate analysis measures of normality are

also reported. Measures of skewness and kurtosis statistics are provided. Based on the central limit theorem, the assumption is made that if the data sampled approximates normality then the sampling distribution is also expected to be normal (Field, 2012). The typical test of normality in terms of skewness and kurtosis is to convert scores to z-scores by subtracting the mean of the distribution (in this case the standard error) and then dividing by the standard deviation. These are taken to be significant if their values are greater (in absolute value) than 1.96, at the 5% level of significance, and 2.58, at the 1% level of significance (Field, 2009). The report of the univariate results of the South African academic researcher sample now follows. First, the univariate statistics of the sample's biographical and contextual factors are reported. This is followed by a report on the univariate statistics that relate to productivity, personality, motivational values, work climate perception and Human Capital Investments (HCI).

5.2.1.1 Descriptive Statistics

In this section, the univariate descriptive statistics for biographical variables are reported. These include age, gender, years of experience, nationality, language, marital status and number of children supported. These statistics are reported in tables, below.

Table 22: Descriptive statistics: Academic researcher sample

Variable	Mean*	Standard Deviation	Variance	Skewness	Kurtosis
Age	46.69	12.139	147.362	.238	-.825
Gender (1 = male)	44.6%	-	-	-	-
Nationality1 (1 = SA) +	74.6%	-	-	-	-
Nationality2 (1 = other) +	25.4%				
Language1 (1=English)	61.7%	-	-	-	-
Language2 (1=Afrikaans)	21.0%	-	-	-	-
Language3 (1 = OtherSA) +	7.2%	-	-	-	-
Language 4 (1 = Foreign)	10.1%	-	-	-	-
Field1 (1 = CLM) +	16.2%	-	-	-	-
Field 2 (1 = Sciences)	27.6%	-	-	-	-
Field 3 (1 = Humanities)	28.1%	-	-	-	-
Field 5 (1 = Health)	26.9%	-	-	-	-
ISI/IBSS/Scopus Articles+	30.27	57.333	3287.073	3.678	18.101
DOHET Articles +	17.20	44.259	1958.819	4.723	26.886
Total Articles	43.40	87.705	7692.	3.974	20.668
Years	15.545	11.950	142.810	.979	.238

Variable	Mean*	Standard Deviation	Variance	Skewness	Kurtosis
Title1 (1 = Mr./Mrs./Ms.)	24.9%	-	-	-	-
Title2 (1 = Dr.)	36.5%	-	-	-	-
Title3 (1 = Associate/Adjunct Professor)	16.0%	-	-	-	-
Title4 (1 = Professor)	22.3%	-	-	-	-
Marital Status (1=yes)	65.9%	-	-	-	-
Children	1.07	1.216	1.478	1.124	1.797

*means of binary variables above are reported as percentages.

+SA: South Africa

+ OtherSA: one of the 11 official languages of South Africa that is not English, nor Afrikaans.

+CLM: Commerce, Law and Management

+ ISI/IBSS: Institute for Scientific Information/International Bibliography of Social Sciences

+DOHET: Department of Higher Education and Training

5.2.1.2 Productivity

Research productivity was measured by a ratio. This ratio was calculated by dividing a total number of published journal articles over a total number of years of experience as an academic researcher.

Table 23: Research Productivity

Variable	Mean	Standard Deviation	Variance	Skewness	Kurtosis
Total Articles	43.40	87.705	7692.	3.974	20.668
Years	15.545	11.950	142.810	.979	.238
Productivity	2.172	3.189	10.172	2.805	8.793

5.2.1.3 Scale measures

Descriptive statistics pertaining to measures of personality, motivational values, work climate perception and technological propensity are provided in Table 24, below. Collectively, these variables are referred to as the Human Resources Management (HRM) determinants

Table 24: Human Resources Management (HRM) determinants

Variable*		Mean	Median	Std. Deviation	Variance
Personality					
PersA	Agreeableness	4.708	4.800	1.328	1.765
PersE	Extraversion	4.306	4.250	1.320	1.743

Variable*		Mean	Median	Std. Deviation	Variance
PersC	Conscientiousness	4.637	5.000	1.476	2.180
PersO	Openness to Experience	4.800	5.000	1.197	1.435
PersN	Neuroticism	3.408	3.400	1.194	1.427
Motivational Values					
MotST	Self-Transcendence	5.077	5.200	.709	.503
MotOC	Openness to Change	4.097	4.166	.888	.789
MotC	Conservation	4.002	4.000	.982	.966
MotSE	Self-Enhancement	3.516	3.500	.987	.976
Work Climate Perceptions					
ClimRef	Reflexivity	2.477	2.600	.579	.336
ClimOF	Outward Focus	2.948	3.000	.656	.431
ClimForm	Formalisation	2.661	2.600	.484	.234
ClimIF	Innovation & Flexibility	1.946	2.000	.353	.286
ClimTrad	Tradition	2.419	2.333	.732	.537
	Organisational Climate Model (OCM) components				
ClimIPM	Internal Process Model (IPM)	2.540	2.566	.481	.232
ClimOSM	Open Systems Model (OSM)	2.459	2.511	.487	.238
Technological Propensity					
TPTFD	Tolerance for Disruption	3.369	3.250	.585	.343
TPTU	Technology Use	2.793	2.750	.633	.402
TPCP	Crowd propensity	2.934	3.000	.666	.444
TPOO	Open Orientation	3.659	3.750	.627	.394
TPCollabP	Collaborative Propensity	3.541	3.500	.798	.638
TP (Ave)	Technological Propensity (Ave)	3.259	2.350	.431	.187

* Abbreviations were used during analysis to improve ease of reporting. These are listed in the first column of this table. The second column lists the full terms that have been abbreviated.

Table 24 above depicts the descriptive statistics relating to the human resources determinants of personality, motivational values, work climate perceptions and technological propensity. The mean values of each of the sub-components of these determinants are represented in the third column. Median scores are represented in the fourth column. Standard deviations and variance are represented in the fifth and sixth columns, respectively.

Having reported the univariate statistics relating to the variables under study, bivariate correlations are now reported.

5.2.2 Bivariate correlations

Tests of bivariate correlation were conducted. Correlations are not used to test hypotheses, only to provide insight and further information for the interpretation of multivariate findings. However, this section is structured according to hypotheses for ease of reporting. Correlation measures the magnitude and direction of a relationship between variables. Multiple and partial correlation analysis extend the same notion between a single variable and a set of variables (Field, 2012). The correlation coefficient may take on any value between +1 and -1 (Field, 2012). The sign of the correlation coefficient (+/-) defines the direction of the relationship, either positive or negative. The following tables report the results of a test of Spearman's rank correlation coefficient, also known as Spearman's Rho, which is a non-parametric measure of rank correlation, or the statistical dependence between two ranking variables (Field, 2012).

5.2.2.1 Technological Propensity and Productivity

The test for correlation between technological propensity and productivity is summarised in Table 25, below.

Table 25: Correlations between technological propensity and productivity

Technological propensity	Years	Articles	Productivity
Tolerance for Disruption	-	-	-
Technological Use	-	-	-
Crowd Propensity	-.214**	-.203**	-.162**
Open Orientation	-	-	-
Collaborative Propensity	.149**	.242**	.230**
Technological propensity (Ave)	-	-	-

** - significant at the 0.05 level (1-tailed)

This table shows there is no significant correlation between technological propensity and productivity.

5.2.2.2 Personality and Technological Propensity

The test for correlation between personality and technological propensity is summarised in Table 26, below.

Table 26: Correlations between personality and technological propensity

Technological propensity	Openness	Neuroticism	Conscientiousness	Agreeableness	Extraversion
Tolerance for Disruption	-	-.104*	-	-	-
Technological use	.111*	-	-	-.102*	-
Crowd Propensity	-	-	-	-	-
Collaborative Propensity	.106*	-.160**	-	-	.127*
Open Orientation	-	-	-	-	-
Technological propensity (Ave)	.096*	-	-	-	-

*significant at the 0.01 level (2-tailed)

**significant at the 0.05 level (1-tailed)

Openness to experience correlates significantly with technological propensity (Spearman's Rho=.096*). Neuroticism, conscientiousness, agreeableness and extraversion do not significantly correlate with technological propensity.

5.2.2.3 Motivational Values and Technological Propensity

The test for bivariate correlation between motivational values and technological propensity is summarised in Table 27, below.

Table 27: Correlations between motivational values and technological propensity

Technological propensity	Self-Transcendence	Openness to Change	Conservation	Self-Enhancement
Tolerance for Disruption	.177**	.300**	-.122**	-
Technological Propensity	-	.109*	-	.142**
Crowd Propensity	.110*	.137*	-.101*	-
Collaborative Propensity	.159**	.226**	-.189**	-.120*
Open Orientation	.144**	.249**	-.154**	-
Technological propensity (Ave)	.171**	.321**	-.203**	-

*significant at the 0.01 level (2-tailed)

** - significant at the 0.05 level (1-tailed)

Self-transcendence and openness to change are both found to be positively correlated with the technological propensity average score. Conservation is found to be negatively associated with

technological propensity and self-enhancement is not significantly associated with technological propensity.

5.2.2.4 Work Climate Perceptions and Technological Propensity

The test for correlation between work climate perceptions and technological propensity is summarised in Table 28, below.

Table 28: Correlations between work climate perceptions and technological propensity

Technological propensity	Reflexivity	Outward Focus	Formalisation	Innovation & Flexibility	Tradition	IPM	OSM
Tolerance for Disruption	-	.093*	-	-	-	-	-
Technological Propensity	-	-	-	-	-	-	-
Crowd Propensity	-	-	-	-	-	-	-
Collaborative Propensity	-	.092*	-	-	-	-	-
Open Orientation	-	-	-	-	-	-	-
Technological propensity (Ave)	-	-	-	-	-	-	-

*significant at the 0.01 level (2-tailed)

None of the constructs of work climate perception are significantly correlated with technological propensity.

5.2.2.5 HCI and Technological Propensity

The test for bivariate correlation between HCI and technological propensity is summarised in Table 29, below.

Table 29: Correlations between HCI and technological propensity

Technological propensity	Experience
Tolerance for Disruption	-
Technological Propensity	-
Crowdsourcing and Crowdfunding Propensity	-.214**
Open Orientation	-

Collaborative Propensity	.149**
Technological propensity (Ave)	-

** - significant at the 0.05 level (1-tailed)

Years of experience (or, HCI) does not significantly correlated with technological propensity.

5.2.2.6 HCI and Productivity

The test for bivariate correlation between HCI and Productivity is summarised in Table 30, below.

Table 30: Correlations between HCI and Productivity

HCI	Years	Articles	Productivity
Years of Experience	1.000	.702**	.353**

** - significant at the 0.05 level (1-tailed)

HCI (measured by years of experience) was found to be significantly correlated with productivity. Exploratory factor analyses (EFAs) were conducted as tests of discriminant and convergent validity. These are reported next.

5.2.3. Tests of Discriminant and Convergent Validity

Exploratory Factor Analyses (EFAs) were conducted on the TIPI, PVQ, OCM and technological propensity scales respectively, to test for discriminant and convergent validity (Campbell & Fisk, 1959). Field (2012) suggests that a sample size over 300 is generally considered adequate for a Factor Analysis. Exploratory Factor Analysis was conducted to identify correlations between observations that stem from their relationship to latent variables in the data, each of which takes the form of a linear model (Field, 2012). Prior to each EFA, a process of data screening was conducted, to detect any problematic inter-correlation between variables and issues relating to singularity (Field, 2012). The respective details of the data screening and subsequent exploratory factor analyses performed on the TIPI, PVQ, OCM and technological propensity scales now follow.

5.2.3.1 Personality (The Modified TIPI scale)

A correlation matrix was used to check the patterns of relationships. The correlation matrix provided a determinant of 0.664, ($p<0.00001$), indicating that multi-collinearity was not a threat to interpretation (Field, 2012), that all data gathered through the modified TIPI scale correlated relatively well and none of the correlation coefficients were too large. Kaiser (1974) suggests accepting KMO values greater than 0.5, as an indication of the appropriateness of the factor analysis. Bartlett's test of sphericity tests the null hypothesis that the original correlation matrix is an identity matrix (Field, 2012). The KMO measure of sampling adequacy returned a value of .687, which indicates that this test was indeed appropriate. Bartlett's Test was shown to be significant ($p<.000$; $<.05$). Principal axis factoring was used to produce a table of communalities, with two columns showing correlations for items before and after extraction. Initial communalities are, for correlation analyses, the proportion of variance accounted for in each variable by the rest of the variables (Field, 2012). The second column shows extraction communalities (after extraction), which are estimates of the variance in each variable accounted for by the factors in the factor solutions. Small values (<.3) indicate variables that do not fit well with the factor solution and should possibly be dropped from the analysis. In this case, before extraction, 25 linear components were discovered in the data that matched the 25 items measured in the modified TIPI scale. After extraction, seven of these items were found to have extraction communalities or had values of >.3. These included O3, A4, E5, O5, A1, C2, C4 and O4. Since the components of personality (extraversion, agreeableness, neuroticism, conscientiousness and openness to experience) are theoretically unrelated (they do not measure the same thing), principal axis factoring with Varimax rotation was used. This method of factoring assumes orthogonal (or, unrelated) relationships between constructs, as in the case of any Big Five personality measure. This rotated factor matrix produced 8 latent factors, or eight factors that were shown to have eigenvalues greater than 1. The cumulative variance of these 8 factors accounted for 43.420% of the cumulative variance in the measure, which is relatively low but considered acceptable for opinion-based surveys (Field, 2012). This number of latent factors (or, components) was confirmed by way of a Scree plot which had an inflection point at Factor Number 8, on the x-Axis (See Appendix 8.1)

5.2.3.2 Motivational values (The PVQ)

Principal Axis Factoring was used to analyse the PVQ Scale. Orthogonal rotation was used because it assumes that dimensions are uncorrelated (Field, 2012). For the academic sample, the correlation matrix provides a determinant of 0.002 (p>.00001), indicating that multi-collinearity was not a threat to interpretation. A KMO value of 0.796 (p>0.5) indicates that the factor analysis for PVQ is therefore considered appropriate. Bartlett's test of sphericity is significant (p = .000). Before extraction, 21 linear components were discovered within the data. After extracting all factors with eigenvalues greater than 1, four factors remained. The cumulative variance of these accounted for 43.834%, which is considered suitable for opinion-based surveys (Field, 2012). Motivational values were tested using Principal Axis Factoring analysis, since this method assumes that all variance is not common (Field, 2012). Several items associated with extraction communalities were identified, including Universalism1, Self-Direction2 and Universalism3. Orthogonal rotation was used, as the constructs of the PVQ (motivation) are purported to be theoretically uncorrelated. The rotated factor matrix produced five factors, or latent variables (with eigenvalues greater than one), in contrast to Schwartz's (2012) four higher-order values, confirmed by the inflection point on the corresponding Scree plot.

5.2.3.3 Technological Propensity (The Technological Propensity Scale)

Principal component factoring, with no rotation was used to analyze the technological propensity scale, since the items in the scale and theoretically similar, all measuring the components of technological propensity. For the academic researcher sample, the correlation matrix produced a determinant of 0.51 (p>0.0001), indicating correlation coefficients that are not too large or multi-collinear. The KMO value of .819>0.5, appropriately indicated the factor analysis. Bartlett's Test of Sphericity produced a significant result, p<0.000. Before extraction, 20 linear components (factors) were discovered within the technological propensity data; after extraction, this number decreased to 4, following the removal of all factors with eigenvalues greater than 1. The cumulative variance accounts for 51.623%, considered suitable for opinion-based surveys (Field, 2012). In assessment of prior and post extraction communalities, no items were found to have extraction communalities >0.3: CCP1, CCP2, TP3, TP4, TP1, TP2 and TFD3. The component factor matrix (and corresponding Scree plot inflection point) produced extraction of 6 factors, or latent variables with eigenvalues greater than 1.

5.2.3.4 Work Climate Perceptions (The OCM)

Assuming orthogonal relationships between climate scale items, principal axis factoring was used to determine latent constructs in the Organizational Climate Model (OCM). The correlation matrix produced a determinant of .001 ($p<.0001$). Tests of appropriateness and sphericity both returned significant values, KMO= .876 and Bartlett's test, $p=0.000$, respectively. Post-extraction, communalities were discovered in only 1 item; OF1, while all other items had extraction communalities > .3. Varimax rotation with Kaiser normalisation which produced a rotated factor matrix with five latent constructs (confirmed with corresponding Scree plot), with cumulative variance of 44.690%. Items with eigenvalues greater than one were loaded onto five factors. Having reported the results of exploratory factor analyses, the results of the multivariate analyses are now reported. Results of multivariate testing are now reported, as follows.

5.2.4 Multivariate Analysis: Regression, Mediation and Moderation Analyses

Regression covariates were chosen on the basis of theory. EFAs were conducted to test for singularity and potential multicollinearity of regression covariates. In all regression models, VIF values were below 10 and Tolerance values were above .20, indicating that multi-collinearity was not to be taken as a threat to interpretation (Field, 2012). All tests of regression, mediation and moderation were bootstrapped. Table 31 below, provides a list of covariates that were chosen for inclusion in regression models, for the academic researcher sample.

Table 31: Covariate selection for academic researcher sample

Covariate Code*	Covariate Name	Description
Gender	Gender	Male or female
Nat1SA	Nationality (South African)	South African respondents
Lan1English	Language (English)	Respondents that speak English as a first language
Lan3OtherSA	Language (isiZulu, isiXhosa, Northern Sotho, Southern Sotho, Tswana, Venda, Tsonga, Swati or Ndebele)	Respondents that speak one of the 9 official languages of South Africa, other than English or Afrikaans
Children	Children	The number of dependent children supported in the respondent's family

Field2Sciences	Field of study (Sciences)	Respondents whose research could be categorised as the broad area of 'the sciences'
Field3Humanities	Field of study (Humanities)	Respondents whose research could be categorised as the broad area of 'the humanities'
Covariate Code*	**Covariate Name**	**Description**
Years of Experience	Years of experience	The number of years of experience the respondent has as an academic researcher
ClimIPM	Climate (Internal Process Model)	Internal Process Model (IPM) climates: Measure of inwardly focused work climate perceptions
ClimOSM	Climate (Open Systems Model)	Open Systems Model (OSM) climates: Measure of outwardly focused work climate perceptions

* For ease of reporting, abbreviated covariate codes (listed in the first column) are used for equations and specifications henceforth.

5.2.4.1 Hypothesis A1: Technological propensity is significantly associated with productivity

The primary research question of this study is as follows:

What is the relationship between technological propensity and productivity?

For the South African academic researcher sample, productivity was calculated as a productivity ratio (total number of journal publications over total years of experience as an academic researcher). Technological propensity was measured by the technological propensity scale, which was derived from the literature. The technological propensity scale measures the extent to which individuals seize new technological opportunities (such as crowdsourcing) that provide significant economies of scale. Tests of hierarchical multiple regression were conducted to determine the extent of the relationship between technological propensity and productivity, with the inclusion of the covariates listed above. Full SPSS output of each test of multiple hierarchical regression is included in Appendix 8.1. In accordance with precedent, all dependent variables were transformed using a natural log transformation (Gujarati & Porter, 2009; Field, 2012) prior to each test of regression.

A test of regression was conducted to assess Hypothesis A1. Technological propensity is found to be not significantly associated with productivity. The results of the test of regression

produced two models. In model 1, covariates accounted for a total of 14.9% of variance in the model (R^2 = .149; p<.000). Following the inclusion of technological propensity as an independent variable in model 2, R^2 change was minimal (.006). Technological propensity was found to contribute a non-significant amount of variance to the regression model (R^2 = .154; p=.115). Both regression models are shown to be significant and a 'good fit' (p<.001). The specification is represented as follows:

Y(Productivity) = .326 +.261(Gender) -.122(Nat1SA) +.233 (Lan1Eng) -.117(Lan3OtherSA) +.028(Children) +.044(Field2Sciences) -.403(Field3Humanities) +.021(Years) -.189(ClimIPM) -.279(ClimOSM) +.204(technological propensity)

Significant standardised coefficients include the following: Gender (113; p<.032), Field3Humanities (-.159; p<.003), Years of Experience (.215; p<.000) and ClimOSM (-.118; p<.027). The independent variable, technological propensity (.077; p<.115) is not significantly associated with productivity. On the basis of these results, the null hypothesis is not rejected. Technological propensity is not significantly associated with productivity.

5.2.4.2 Hypothesis A2: Personality is significantly associated with technological propensity

Personality was measured using a modified version of the TIPI scale. The Big Five Personality constructs, including Openness to Experience (PersO), Extraversion (PersE), Conscientiousness (PersC), Neuroticism (PersN) and Agreeableness (PersA) were however, not significantly associated with technological propensity. Each of these constructs (represented by abbreviations above) was tested for association with technological propensity, as per the tests described below:

5.2.4.2.1 Hypothesis A2.1: Openness to Experience is significantly associated with technological propensity

The test for association between Openness to Experience (PersO) and technological propensity produced a significant result. The R^2 value for Model 1 (covariates only) is non-significant (.025; p<.365). The inclusion of PersO as a predictor increases the R^2 value to .041 (p=.010),

making for a significant R^2 change of .015, or an increase in 1.5% of variance. The specification is represented as follows:

> Y(Technological Propensity) = 1.127 -.014(Gender) -.033(Nat1SA) +.003(Lan1Eng) -.010 (Lan3OtherSA) +.000(Children) +.008 (Field2Sciences) -.013 (Field3Humanities) -.001 (Years) -.003 (CLimIPM) +.006(ClimOSM) +.014(PersO).

Significant standardised coefficients includes only Nationality (-.109; p<.026) and Openness to Experience (PersO) (.127; p<.010). On the basis of this analysis, the null hypothesis is rejected. Openness to experience is significantly associated with technological propensity.

5.2.4.2.2 Hypothesis A2.2 Extraversion is significantly associated with technological propensity

Extraversion (PersE) is found to be not significantly associated with technological propensity. The inclusion of covariates in the model contributes 2.5% (R^2=.025; p<.365) of total variance. The inclusion of the predictor PersE accounts for an additional non-significant.1% of variance (R^2 Change=.001; p<.625). The specification is presented as follows:

> Y(Technological Propensity) = .179 -.016(Gender) -.033(Nat1SA) +.002(Lan1Eng) -.016(Lan3OtherSA) .000(Children) +.011(Field2Sciences) -.008(Field3Humanities) -.001(Years) +.005(ClimIPM) +.006(ClimOSM) +.002(PersE).

Of the standardised coefficients, only Nat1SA (-.108; p<.030) is significant. The independent variable, PersE (.024; p<.625) is not significant. On the basis of this result, the null hypothesis is not rejected. Extraversion is not significantly associated with technological propensity.

5.2.4.2.3 Hypothesis A2.3 Conscientiousness is significantly associated with technological propensity

Conscientiousness (PersC) is found to not be significantly associated with technological propensity. The inclusion of covariates in the model account for a non-significant 2.5% of total

variance (R^2 = .025; p<.365). The inclusion of PerC only adds a further .1% of variance to the model (R^2 change = .001). Neither of these models are significant (p>.000). The specification is represented as follows:

> Y(Technological Propensity) = +1.172 -.016 (Gender) -.033(Nat1SA) +.002(Lan1Eng) -.017 (Lan3OtherSA) +.000(Children) +.009(Field2Sciences) -.001(Field3Humanities) -.001(Years) +.006(ClimIPM) +.006(ClimOSM) +.003(PersC).

The only standardised coefficients that is significant is NatSA (-.108; p<.030). Conscientiousness (.037; p<.457) is not significant. Based on this analysis, the null hypothesis is not rejected. Conscientiousness is not significantly associated with technological propensity.

5.2.4.2.4 Hypothesis A2.4 Neuroticism is significantly associated with technological propensity

All coefficients account for 2.5% of variance in the model (R^2 = .025; p<.365). The inclusion of Neuroticism (PersN) accounts for an additional 1% of significant variance. (R^2 = .036; p<.034). The specification is represented as follows:

> Y(Technological Propensity) = +.1.234 -.019(Gender) -.033(Nat1SA) +.005(Lan1Eng) -.019(Lan3OtherSA) -.001(Children) +.011(Field2Sciences) -.006(Field3Humanities) -.001 (Years) +.005(ClimIPM) +.005(ClimOSM)-.012 (PersN).

Of the standardised coefficients, only NatSA (-.108; p<.029) and PersN (-.105; p<.034) are significant. Based on this analysis, the null hypothesis is rejected. Neuroticism is significantly associated with technological propensity.

5.2.4.2.5 Hypothesis A2.5 Agreeableness is significantly associated with technological propensity

Agreeableness (PersA) is found to not be significantly associated with technological propensity. All coefficients account for 2.5% of variance in the model. The inclusion of

agreeableness accounts for a further.1% of total variance (R^2change = .001; p<.680). Neither of these contributions are significant (p>.000). The specification is represented as follows:

Y(Technological Propensity) = +1.197 -.017(Gender) -.033(Nat1SA) +.003(Lan1Eng) -.018 (Lan3OtherSA) +3.699E-5(Children) +.011 (Field2Sciences) - .008 (Field3Humanities) -.001 (Years) + .006(ClimIPM) +.006(ClimOSM)-.002 (PersA).

Nat1SA (-.110; p<.027) is the only significant standardised coefficient. No other covariates, nor the predictor variable Agreeableness (-.021; p<.680) are significant. The null hypothesis is not rejected. Agreeableness is not significantly associated with technological propensity. The results of regression testing for Hypothesis A2 are summarised in Table 32, below.

Table 32: Results of regression testing for Hypothesis A2: Personality is associated with technological propensity

Personality	R^2 (Model 1)	R^2 (Model 2)	R^2 Change	Null hypothesis	Direction
Openness to Experience	.025 (p<.365)	.041 (p<.010)	.015	Rejected	Positive (.127; p<.010)
Extraversion	.025 (p<.365)	.026 (p<.625)	.001	Not rejected	-
Conscientiousness	.025 (p<.365)	.027 (p<.457)	.002	Not rejected	-
Neuroticism	.025 (p<.365)	.036 (p<.034)	.010	Rejected	Negative (-.105; p<.034)
Agreeableness	.025 (p<.365)	.026 (p<.680)	.001	Not rejected	-

5.2.4.3 Hypothesis A3: Motivational Values are significantly associated with technological propensity

Motivational values were measured using Schwartz's (2012) Motivational Values framework. According to Schwartz (2006), the framework comprises of four higher-order values. These include i) self-transcendence, ii) openness to change, iii) conservation and iv) self-enhancement. Each of these was tested for association with technological propensity. The results of these tests are reported as follows.

5.2.4.3.1 Hypothesis A3.1: Self-Transcendence is significantly associated with technological propensity

Coefficients account for 2.5% of variance in the model. The inclusion of self-transcendence (MotST) as a predictor in the model accounts for a total of .055 (R^2 = .055; p<.000), a significant increase of 3%. The specification is represented as follows:

> Y(Technological Propensity) = 1.000-.008(Gender) -.032(Nat1SA) +.004(Lan1Eng)) -.007(Field3Humanities) -.001 (Years)+.010 (ClimIPM) + .004(ClimOSM) +.035(MotST)

Of the standardised coefficients, Nat1SA (-.105; p<.032) and MotST (.180; p<.000) are significant. On the basis of this regression, the null hypothesis is rejected. Self-transcendence is significantly, negatively associated with technological propensity.

5.2.4.3.2 Hypothesis A3.2: Openness to Change is significantly associated with technological propensity

The inclusion of openness to change (MotOC) accounts for a total of 9.3% of variance in the total model (R^2 = .119; p<.000), over the initial 2.5% contributed by coefficients. The specification is represented as follows:

> Y(Technological Propensity) = 1.001-.006(Gender) -.028(Nat1SA) +.005(Lan1Eng) -.046(Lan3OtherSA) +.001 (Children) +.009(Field2Sciences) -.009(Field3Humanities) -.001 (Years) +.001 (ClimIPM) +.002(ClimOSM) +.048(MotOC)

As a standardised coefficient, MotOC has a value of .316 (p<.000). On the basis of this analysis, the null hypothesis is rejected. Openness to change is significantly associated with technological propensity.

5.2.4.3.3 Hypothesis A3.3: Conservation is significantly associated with technological propensity

Conservation (MotC) is found to be associated negatively and significantly with technological propensity. Covariates account for 2.5% of variance in the model. The inclusion of MotC accounts for an additional 5% (R^2 Change =.050). The specification is represented as follows:

> Y(Technological Propensity) = 1.326-.014(Gender) -.026(Nat1SA) -.004 (Lan1Eng) -.8.560E-5(Lan3OtherSA) +.001 (Children) +.002(Field2Sciences) -.021(Field3Humanities) -.001 (Years) +.000(ClimIPM) +.013(ClimOSM) -.033(MotC)

Of the standardised coefficients, years of experience (-.126; p<.015) and MotC (Conservation) are significant (-.242; p<.000). On the basis of this analysis, the null hypothesis is rejected. Conservation is significantly associated with technological propensity.

5.2.4.3.4 Hypothesis A3.4: Self-Enhancement is significantly associated with technological propensity

Self-enhancement (MotSE) is not found to be significantly associated with technological propensity. MotSE accounts for no variance in the model (R^2 = .025; p<.863), over above that of covariates (R^2 change = .000). The specification is represented below:

> Y(Technological Propensity) = 1,193-.017(Gender) -.003(Nat1SA) +.002(Lan1Eng) -.017(Lan3OtherSA) +.7.030E-5 (Children) +.010(Field2Sciences) -.008(Field3Humanities) -.001 (Years) +.006 (ClimIPM) +.006(ClimOSM) -.001(MotSE)

Of the standardised coefficients, only Nat1SA (-.108 p<.029) is significant. Self-enhancement (-.009; p<.863) is not significant. The null hypothesis is not rejected. Self-Enhancement is not significantly associated with technological propensity. The results of the regression testing for Hypothesis A3 are summarised in Table 33, below

Table 33: Results of Regression Testing for Hypothesis A3: motivational values are associated with technological propensity

Motivational Values	R^2 (Model 1)	R^2 (Model 2)	R^2 Change	Null Hypothesis	Direction
Self-Transcendence	.025 (p<.365)	.056 (p<.000)	.030	Rejected	Positive (.180; p<.000)
Openness to Change	.025 (p<.365)	.119 (p<.000)	.093	Rejected	Positive (.316; p<.000)
Conservation	.025 (p<.365)	.075 (p<.000)	.050	Rejected	Negative (-.242; p<.000)
Self-Enhancement	.025 (p<.365)	.025 (p<.863)	.000	Not rejected	-

5.2.4.4 Hypothesis A4: Work Climate is significantly associated with technological propensity

Using Patterson et al.'s (2005) organisational climate model (OCM) which typifies work climates according to their innovative potential, two sub-models were measured. These include the Internal Process Model (IPM) and the OSM (Open Systems Model). These two models exist on opposite ends of the work-climate spectrum. IPM is generally associated with low-level innovation, while the OSM is generally associated with higher level of innovation. Each of these measurements were tested for association with technological propensity.

5.2.4.4.1 Hypothesis A4.1: IPM is significantly associated with technological propensity

The association between technological propensity and IPM is not significant. The inclusion of IPM (ClimIPM) in the model accounts for no further variance (R^2 change = .000). The specification is represented as follows.

> Y(Technological propensity) = 1.217 -.016 (Gender) -.031(Nat1SA) +.001 (Lan1Eng) -.020 (Lan3OtherSA) +.000(Children) +.008 (Field2Sciences) -.010 (Field3Humanities) -.001 (Years) +.000(IPM)

As a standardised coefficient, only NatSA (-.103; p<.037) is significant. IPM (.000; p<.993) is not significant. No other standardised coefficients are significant. The null hypothesis is not rejected. IPM is not significantly associated with technological propensity.

5.2.4.4.2 Hypothesis A4.2: OSM is significantly associated with technological propensity

The association between OSM and technological propensity is also not significant. The inclusion of OSM (ClimOSM) in the model accounts for no increase in variance in the model (R^2 change = .000). The specification is represented as follows:

> Y(Technological Propensity) = 1.206 -.017(Gender) -.033(Nat1SA) +.003 (Lan1Eng) -.016 (Lan3OtherSA) +.7.334E-5(Children) +.011 (Field2Sciences) -.008 (Field3Humanities) -.001 (Years) +.004 (OSM)

The only significant standardised coefficient is NatSA (-.109; p<.028). No other standardised coefficients are significant. The independent variable, OSM (.016; p<.745) is not significant. Based on this analysis, the null hypothesis is not rejected. OSM is not significantly associated with technological propensity. The results of regression testing for Hypothesis A4 are summarised in Table 34, below.

Table 34: Results of Regression Testing for Hypothesis A4: work climate perceptions are associated with technological propensity

Work Climate	R^2 (Model 1)	R^2 (Model 2)	R^2 Change	Null Hypothesis	Direction
Internal Process Model (IPM)	.023 (p<.425)	.023 (p<.993)	.000	Not rejected	-
Open Systems Model (OSM)	.025 (p<.221)	.025 (p<.745)	.000	Not rejected	-

5.2.4.5 Hypothesis A5: Personality mediates the relationship between technological propensity and productivity

Tests of mediation were conducted to investigate the mediating effect of personality on the relationship between technological propensity and productivity. All tests of mediation were conducted using Hayes' (2013) PROCESS plug-in for SPSS. All tests of mediation were bootstrapped at 5 000 iterations. All tests of mediation included the same list of covariates as were used for tests of regression. In assessing the mediating effect of personality on the relationship between technological propensity and productivity, each of the Big Five Personality traits were tested individually. These include openness to experience, extraversion,

conscientiousness, neuroticism and agreeableness. Dependent variables were transformed prior to analysis, using a natural log transformation, as per precedent (Field, 2012).

5.2.4.5.1 Hypothesis A5.1: Openness to Experience mediates the relationship between technological propensity and productivity

Hayes' (2013) PROCESS for SPSS follows a specific format when testing for mediation, which is now described and used for all subsequent tests of mediation in this study. First, PROCESS assesses if a predictor variable, (in this case technological propensity) does indeed predict the mediator (in this case, PersO). In this case, technological propensity does not predict PersO (.265; p<.073).

Next, PROCESS checks if the predictor (technological propensity) and the mediator (PerO) predict the dependent variable (productivity). In this case, the predictor variable, technological propensity (.176; p<.147) does not significantly predict productivity. However, the mediator, PersO (.105; p<.044) does predict productivity. Interestingly, some of the covariates included in the analysis are found to significant predictors of productivity. These include Gender (.280; p<.022), Field3Humanities (-.432; p<.001), years of experience (.020; p<.000) and ClimOSM (-.286; p<.028).

Next, PROCESS checks the indirect effects of the predictor (technological propensity) on the dependent variable (productivity). This is the test of mediation, or the indirect effect of technological propensity on productivity *through* PersO. To check for significance, PROCESS provides bootstrapped confidence intervals (BootCIs). If the interval contains zero, it is not a significant mediation. If it does not contain zero, then it is significant mediation. Here, the BootCI [.000; .093] does indeed contain zero and therefore, the mediation effect of PersO is not significant (.028; p>.000). On the basis of this result, the null hypothesis is not rejected. Openness to experience does not mediate the relationship between technological propensity and productivity.

5.2.4.5.2 Hypothesis 5A.2: Extraversion significantly mediates the relationship between technological propensity and productivity

Technological propensity (.144; p<.381) does not predict Extraversion (PersE). Of the covariates included in the model, only Gender (-.594; p<.000) and years of experience (.017; p<.006) are significant predictors of PersE. PersE (.087; p<.031) does predict productivity. Technological propensity (.191; p<.124) does not predict productivity. Several covariates are found to be significant predictors of productivity. These include Gender (.312; p<.012), Field3Humanities (-.385; p<.004), years of experience (.020; p<.000) and ClimOSM (-.280; p<.031). The mediating effect of PersE (.012) is not significant, since BootCI [-.010; .060]. Thus, the null hypothesis is not rejected. Extraversion is not a significant mediator of the relationship between technological propensity and productivity

5.2.4.5.3 Hypothesis A5.3: Conscientiousness significantly mediates the relationship between technological propensity and productivity

Technological propensity does not predict conscientiousness (PersC) (.111; p<.523). Of the covariates, only Field2Sciences (.451; p<.021) significantly predicts the mediator PersC. Technological propensity (.201; p<.107), and PersC (.029; p<.461) do not significantly predict productivity. Several covariates however, are found to significantly predict the dependent variable. These include Gender (.265; p<.032), Field3Humanities (-410; p<.003), years of experience (.021; p<.000) and ClimOSM (-.275; p<.033). The mediating effect of PersC (.003) is not significant, since BootCI [-.005; .038]. Therefore, the null hypothesis is not rejected. Conscientiousness does not significantly mediate the relationship between technological propensity and productivity.

5.2.4.5.4 Hypothesis A5.4: Neuroticism significantly mediates the relationship between technological propensity and productivity

Technological propensity does not predict neuroticism (PersN) (-.282; p<.058). Significant covariates include only Years of experience (-.014; p<.010) PersN (-.071; p<.131) and technological propensity (.184; p<.135) do not significantly predict productivity. However, some covariates do predict productivity. These include Gender (.249; p<.043), Field3Humanities (-.388; p<.004), years of experience (.020; p<.000) and ClimOSM (-.286;

p<.028). The mediating effect of PersN (.020) is not significant since BootCI [-.003; .067]. Thus, the null hypothesis is not rejected. Neuroticism does not significantly mediate the relationship between technological propensity and productivity.

5.2.4.5.5 Hypothesis A5.5: Agreeableness significantly mediates the relationship between technological propensity and productivity

Technological propensity does not predict agreeableness (PersA) (-.008; p<.955). As a covariate, only years of experience (.019; p<.001) is a significant predictor of agreeableness. Agreeableness does not predict productivity (-.057; p<.241). Technological propensity does not predict productivity (.203, p<.097). Covariates that significantly predict productivity include Gender (.249; p<.045), Field3Humanities (-.406; p<.003), years of experience (.022; p<.000) and ClimOSM (-.269; p<.041). The mediating effect of PersA (.000) is not significant since BootCI [-.021; .025]. On the basis of this analysis, the null hypothesis is not rejected. Agreeableness does not significantly mediate the relationship between technological propensity and productivity. The results of mediation testing for Hypothesis A5 are summarised in Table 35, below.

Table 35: Results of Regression Testing for Hypothesis A5: personality mediates the relationship between technological propensity and productivity

Personality	Mediating effect	BootCI*	Null hypothesis	Direction
Openness to Experience	.028	[.000; .093]	Not rejected	-
Extraversion	.012	[-.010; .060]	Not rejected	-
Conscientiousness	.003	[-.005; .038]	Not rejected	-
Neuroticism	.020	[-.003; .067]	Not rejected	-
Agreeableness	.000	[-.021; .025]	Not rejected	-

*Bootstrapped Confidence Intervals

5.2.4.6 Hypothesis A6: Motivational Values mediate the relationship between technological propensity and productivity

Hayes' (2013) PROCESS was used to test mediating effect of motivational values on the relationship between technological propensity and productivity. Like previous tests of

mediation, individual components, including self-transcendence, openness to change, conservation and self-enhancement were all tested individually for their mediating effect. The mediating effect of self-transcendence on the relationship between technological propensity and productivity was conducted as follows.

5.2.4.6.1 Hypothesis A6.1: Self-Transcendence significantly mediates the relationship between technological propensity and productivity

Technological propensity (.312, p<.001) does predict self-transcendence (MotST). Significant covariates predictors of MotST include Gender (-.276; p<.001) and Field2Sciences (-.211; p<.035). MotST (.000; p<.999) and technological propensity (.204; p<.113) do not significantly predict the dependent variable (productivity). Covariates that significantly predict the dependent variable (productivity) include Gender (.261; p<.036), Field3Humanities (-.403; p<.003), years of experience (.021; p<.000) and ClimOSM (-.279; p<.031). The mediating effect of MotST (.000) is not significant since BootCI [-.054; .058]. Based on this analysis, the null hypothesis is not rejected. Self-transcendence does not significantly mediate the relationship between technological propensity and productivity.

5.2.4.6.2 Hypothesis 6A.2: Openness to Change significantly mediates the relationship between technological propensity and productivity

Technological propensity (.666; p<.000) predicts openness to change (MotOC). Covariates that significantly predict MotOC include Gender (-.267; p<.006) and Lan3OtherSA (.600; p<.038). MotOC does predict the dependent variable, productivity (.157; p<.022). Technological propensity (.099; p<.452) does not significantly predict productivity. Significant covariate predictors of productivity include the following: Gender (.303; p<.014), Field3Humanities (-.413; p<.002), years of experience (.021; p<.000) and ClimOSM (-.274; p<.034) The mediating effect of MotOC (.105) is significant since BootCI [.013; .205]. Based on this result, the null hypothesis is rejected. Openness to change does significantly mediate the relationship between technological propensity and productivity.

5.2.4.6.3 Hypothesis A6.3. Conservation mediates the relationship between technological propensity and productivity

Technological propensity does predict conservation (MotC) (-.450; p=<.000). Significant covariate predictors of MotC include Lan1Eng (-.229; p<.025), Field3Humanities (-.354; p<.005), years of experience (-.015; p<.000) and ClimOSM (.261; p<.039). MotC (-.085, p<.223) and technological propensity (.165; p<.197) are not significant predictors of productivity. Significant covariate predictors of productivity include the following: Gender (.266, p<.032), Field3Humanities (-.433, p<.001), years of experience (.020; p<.000) and ClimOSM (-.256; p<.045). The mediating effect of MotC (.038) is not significant since BootCI [-.019; .113]. Therefore, the null hypothesis is not rejected. Conservation does not significantly mediate the relationship between technological propensity and productivity.

5.2.4.6.4 Hypothesis A6.4. Self-Enhancement significantly mediates the relationship between technological propensity and productivity

Technological propensity (-.020, p<.887) does not predict self-enhancement (MotSE). Of the covariates, years of experience (-.011; p<.017) significantly predict self-enhancement. MotSE (.028. p<.604) and technological propensity (.204, p<.100) do not significantly predict productivity. Significant covariate predictors of productivity include Gender (.263; p<.032), Field3Humanities (-.401; p<.003), years of experience (.022; p<.000) and ClimOSM (-.277; p<.033). The mediating effect of MotSE (-.001) is not significant since BootCI [-.025; .012]. The null hypothesis, therefore, is not rejected. Self-enhancement does not significantly mediate the relationship between technological propensity and productivity. The results of regression testing for Hypothesis A6 are summarised in Table 36, below.

Table 36: Results of Regression Testing for Hypothesis A6: motivational values mediate the relationship between technological propensity and productivity

Motivational Values	Mediating effect	BootCI*	Null hypothesis	Direction
Self-Transcendence	.000	[-.054; .058]	Not rejected	-
Openness to Change	.105	[.013; .205]	Rejected	Positive (.105; p<.000)
Conservation	.038	[-.019; .113]	Not rejected	-
Self-Enhancement	-.001	[-.025; .012]	Not rejected	-

* Bootstrapped Confidence Intervals

5.2.4.7 Hypothesis A7: Work-Climate perception mediates the relationship between technological propensity and productivity

The differentiation between Patterson et al.'s (2005) Internal Process Model (IPM) and Open Systems Model (OSM) was tested as a potential mediator on the relationship between technological propensity and productivity. For each model, a different test of mediation was conducted, as follows.

5.2.4.7.1 Hypothesis A7.1 Internal Process Model climates significantly mediate the relationship between technological propensity and productivity

Technological propensity (-.029; p<.676) does not significantly predict IPM. Of the covariates included in the model, only Lan1Eng (.165; p<.005) significantly predicts IPM. IPM (-.085; p<.480) does not predict productivity, nor does technological propensity (.204; p<.099). Significant covariate predictors of productivity include the following: Gender (.271; p<.028), Field3Humanities (-.385; p<.005) and years of experience (.021; p<.000). The mediating effect of IPM (.002) is not significant since BootCI [-.009; .045]. Therefore, the null hypothesis is not rejected. IPM does not significantly mediate the relationship between technological propensity and productivity.

5.2.4.7.2 Hypothesis A7.2 Open Systems Model climates significantly mediate the relationship between technological propensity and productivity

Technological propensity (.014, p<.814) does not predict OSM. The only covariate that significantly predicts OSM is Lan3Other (-.427; p<.001). OSM does not predict productivity (-.213; p<.080) nor does technological propensity (.2015; p<.098). Significant covariate predictors of productivity include Gender (.250; p<.040), Field3Humanities (-.203; p<.003) and years of experience (.022; p<.000). The mediation effect of OSM (-.003) is not significant as BootCI [-.042; .021]. On the basis of this analysis, the null hypothesis is not rejected. OSM does not significantly mediate the relationship between technological propensity and productivity. The results of regression testing for Hypothesis A7 are summarised in Table 37, below.

Table 37: Results of Regression Testing for Hypothesis A7: work climate perceptions mediate the relationship between technological propensity and productivity

Work Climate Perception	Mediating effect	BootCI*	Null hypothesis	Direction
IPM	.002	[-.009; .045]	Not rejected	-
OSM	-.003	[-.042; .021]	Not rejected	-

*Bootstrapped Confidence Intervals

5.2.4.8 Hypothesis A8: Human Capital Investments (HCI) mediate the relationship between technological propensity and productivity

A test of mediation was conducted to assess the potential mediation effect of HCI on the relationship between technological propensity and productivity. Technological propensity (-2.049; p<.130) does not significantly predict HCI. Significant covariate predictors of HCI include Gender (6.406; p<.000), Lang1Eng (3.371; p<.008) and Field2Sciences (4.069; p<.008).

While HCI do significantly predict productivity (.021; p<.000), technological propensity does not (.204; p<.098). Significant covariate predictors of productivity include the following: Gender (.261; p<.034), Field3Humanities (-.403; p<.003) and ClimOSM (-.279; p<.031). The mediating effect of HCI (-.043) is not significant since BootCI [-.115; .006]. Based on this analysis, the null hypothesis is not rejected. HCI do not significantly mediate the relationship between technological propensity and productivity.

5.2.4.9 Hypothesis B1: Human Capital Investments (HCI) are significantly associated with productivity

A test of hierarchical multiple regression was conducted to assess the relationship between HCI and productivity. In the first model, the covariates account for an accumulated 11.2% of total variance (R^2=.112; p<.000). The inclusion of HCI in Model 2 accounts for an additional 3.6% of variance (R^2. =149; p<.000). The specification is represented as follows:

Y(Productivity) = 1.020 +.254(Gender) -.145(Nat1SA) +.237(Lan1Engl) -.138(Lan3OtherSA) +.027 (Children) +.050(Field2Science) -.409(Field3Humanities) -.191(ClimIPM) -.277(ClimOSM) +.021(HCI)

As standardised coefficients, significant covariates include Gender (.110; p<.037), Field3Humanities (-.161; p<.003) and ClimOSM (-.117; p<.028). HCI is found to be a significant predictor of productivity (.208; p<.000). Based on this result, the null hypothesis is rejected. HCI are significantly associated with productivity.

5.2.4.10 Hypothesis B2: Personality mediates the relationship between Human Capital Investments (HCI) and productivity

Further tests of mediation, using Hayes' (2013) PROCESS were conducted to assess the mediating effect of personality on the relationship between HCI and productivity. Each of the Big Five personality traits were tested individually, as follows.

5.2.4.10.1 Hypothesis B2.1: Openness to Experience mediates the relationship between HCI and productivity

HCI (.010; p<.070) do not significantly predict PersO, nor do any of the covariates in the model. PersO (.111, p<032) does predict productivity, as do HCI (.019, p<.000). Significant covariate predictors of productivity include Gender (.276; p<.024), Field3Humanities (-.439; p<.001) and ClimOSM (-.285; p<.031). The mediating effect of PersO (.001) is not significant, since BootCI [.000; .003]. Therefore, the null hypothesis is not rejected. Openness to experience does not mediate the relationship between HCI and productivity.

5.2.4.10.2 Hypothesis B2.2: Extraversion significantly mediates the relationship between HCI and productivity

HCI do predict PersE (.016, p<.008). Only Gender (-.599, p<.000) as a covariate significantly predicts PersE (Extraversion). PersE (extraversion) does predict productivity (.090; p<.025), as do HCI (.019; p<.000). Significant covariate predictors of productivity include the following: Gender (.308; p<.013), Field3Humanities (-.390; p<.004) and ClimOSM (-.278; p<.034). The mediating effect of PersE (.001) is not significant since BootCI [.000; .004]. The

null hypothesis is not rejected. Extraversion does not mediate the relationship between HCI and productivity.

5.2.4.10.3 Hypothesis B2.3 Conscientiousness significantly mediates the relationship between HCI and productivity

HCI (.001; p<.854) do not predict PersC. Significant covariate predictors of PersC include only Field2Sciences (.454; p<.020). HCI predict productivity (.020; p<.000) but PersC (.031; p<.428) does not predict productivity. Significant covariate predictors of productivity include the following: Gender (.258; p<.036), Field3Humanities (-.417; p<.002) and ClimOSM (-.273; p<.036). The mediating effect of PersC (.000) is non-significant since BootCI [000; .001]. Based on these results, the null hypothesis is not rejected. Conscientiousness does not mediate the relationship between HCI and productivity.

5.2.4.10.4 Hypothesis B2.4: Neuroticism significantly mediates the relationship between HCI and productivity

HCI predict PersN (-.014; p<.016). No covariates predict PersN. PersN (-.078; p<.095) does not predict productivity. HCI do predict PersN (.019; p<.000). Significant covariate predictors of productivity include the following: Gender (.241; p<.049), Lang1Eng (.253; p<.048), Field3Humanities (-.393; p<.004) and ClimOSM(-.285; p<.030). The mediating effect of PersN (.001) is not significant since BootCI [.000; .003]. Therefore, the null hypothesis is not rejected. Neuroticism does not mediate the relationship between HCI and productivity.

5.2.4.10.5 Hypothesis B2.5: Agreeableness significantly mediates the relationship between HCI and productivity

HCI (.019, p<.001) do significantly predict PersA. No covariates are significant predictors of PersA. PersA does not significantly predict productivity (-.057; p<.237). HCI do significantly predict productivity (.022; p<.000). Significant covariates predictors of productivity include Field3Humanities (-.412; p<.002), and ClimOSM (-.267; p<.045). The mediation effect of PersA (-.001) is not significant since BootCI [-.003; .001]. Based on this analysis, therefore, the null hypothesis is not rejected. Agreeableness does not mediate the relationship between

HCI and productivity. The results of regression testing for Hypothesis B2 are summarised in Table 38, below.

Table 38: Results of Regression Testing for Hypothesis B2: Personality mediates the relationship between HCI and productivity

Personality	Mediating effect	BootCI*	Null hypothesis	Direction
Openness to Experience	.001	[.000; .003]	Not rejected	-
Extraversion	.000	[.000; .004]	Not rejected	-
Conscientiousness	.000	[000; .001]	Not rejected	-
Neuroticism	.001	[.000; .003]	Not rejected	-
Agreeableness	-.001	[-.003; .001]	Not rejected	-

*Bootstrapped Confidence Intervals

5.2.4.11 Hypothesis B3: Motivational Values mediate the relationship between Human Capital Investments (HCI) and productivity

The mediating effect of motivational values on the relationship between HCI and productivity was tested using Hayes' (2012) PROCESS method. The results of these tests are now discussed.

5.2.4.11.1 Hypothesis B3.1: Self-Transcendence significantly mediates the relationship between HCI and productivity

HCI (.004; p<.188) do not significantly predict MotST. Significant covariate predictors of MotST include GenderCLM (-.286; p<.000) and Field2Sciences (-.202; p<.043). While HCI do predict productivity, (.020; p<.000), MotST does not predict productivity (.026; p<.757). Significant covariate predictors of productivity include the following: Gender (.261; p<.034), Field3Humanities (-.408; p<.003) and ClimOSM (-.287; p<.034). The mediation effect of MotST (.000) is not significant since BootCI [-.001; .001]. The null hypothesis is not rejected. Self-transcendence does not mediate the relationship between HCI and productivity.

5.2.4.11.2 Hypothesis B3.2: Openness to Change significantly mediates the relationship between HCI and productivity

HCI (-.001; p<.801) do not predict MotOC. The only covariate predictors that significantly predict MotOC are Gender (-.290; p<.004) andLan3OtherSA (.532; p<.043). HCI (.021; p<.000) and MotOC (.173; p<.013) predict productivity. Significant covariate predictors of productivity include Gender (.304; p<.005), Field3Humanities (-.416; p<.002) and ClimOSM (-.273; p<.035). The mediation effect of MotOC (.000) is not significant since BootCI [-.002; .001]. Based on the result, the null hypothesis is not rejected. Openness to change does not mediate the relationship between HCI and productivity.

5.2.4.11.3 Hypothesis B3.3: Conservation significantly mediates the relationship between HCI and productivity

HCI (-.014; p<.001) do predict MotC. Significant covariate predictors of MotC include NatSA (.271; p<.020), Lan1Eng (-.237; p<.025), Lan3OtherSA (.502; p<.045), Field3Humanities (-.340; p<.008) and ClimOSM (.257; p<.042). HCI do predict productivity (.019; p<.000) but MotC (-.102; p<.133) does not. Significant covariate predictors of productivity include Gender (.261; p<.035) and Field3Humanities (-.444; p<.001). The mediation effect of MotC (.001) is not significant since BootCI [.000; .004]. On the basis of this result, null hypothesis is not rejected. Conservation does not mediate the relationship between HCI and productivity.

5.2.4.11.4 Hypothesis B3.4: Self-Enhancement significantly mediates the relationship between HCI and productivity

HCI (-.011; p<.017) do predict MotSE. There are no significant covariate predictors of productivity. HCI do precit productivity (.021; p<.000). MotSE does not predict productivity (.028; p<.613). Significant predictor covariates of productivity include the following: Gender (.256; p<.036), Field3Humanities (-.407; p<.003) and ClimOSM (-.275; p<.036). The mediation effect of MotSE (.000) is not significant since BootCI [-.002; .001]. Therefore, the null hypothesis is not rejected. Self-enhancement does not mediate the relationship between HCI and productivity. The results of regression testing for Hypothesis B3 are summarised in Table 39, below.

Table 39: Results of Regression Testing for Hypothesis B3: Motivational values mediate the relationship between HCI and productivity

Motivational Values	Mediating effect	BootCI*	Null hypothesis	Direction
Self-Transcendence	.000	[-.001; .001]	Not rejected	-
Openness to Change	.000	[-.002; .001]	Not rejected	-
Conservation	.001	[.000; .004]	Not rejected	-
Self-Enhancement	.000	[-.002; .001]	Not rejected	-

*Bootstrapped Confidence Interval

5.2.4.12 Hypothesis B4: Work Climate Perceptions mediates the relationship between Human Capital Investments (HCI) and productivity

The mediating effect of climate on the relationship between HCI and productivity was assessed using Hayes' (2013) PROCESS. Both the IPM and OSM were tested for potential mediating effect as follows:

5.2.4.12.1 Hypothesis B4.1: Internal Process Model work climate mediates the relationship between HCI and productivity

HCI (-.004; p<.103) do not predict IPM. No covariates are significant predictors of IPM. HCI predict productivity (.020; p<.000) but IPM (-.090; p<.463) does not. Significant covariate predictors of productivity include Gender (.265; p<.031) andField3Humanities (-.392; p<.004.) The mediating effect of IPM (.000) is not significant since BootCI [.000; .002]. The null hypothesis is not rejected. IPM does not mediate the relationship between HCI and productivity.

5.2.4.12.2 Hypothesis B4.2: Open Systems Model work climate mediates the relationship between HCI and productivity

HCI (.004; p<.076) do predict OSM. Significant covariate predictors of OSM include only Lan3OtherSA (-.428; p<.001). HCI predict productivity (.021; p<.000) but OSM (-.210; p<.084) does not predict productivity. Significant covariate predictors of productivity include Gender (.243; p<.045) and Field3Humanities (-.410; p<.002). The mediating effect of OSM (-.001) is not significant, since BootCI [-.003; .000]. On the basis of this result, the null hypothesis is not rejected. OSM does not mediate the relationship between HCI and

productivity. The results of the regression testing for Hypothesis B4 are summarised in Table 40, below.

Table 40: Results of Regression Testing for Hypothesis B4: Work climate perceptions mediate the relationship between HCI and productivity

Work Climate Perception	Mediating effect	BootCI*	Null hypothesis	Direction
IPM	.000	[.000; .002]	Not rejected	-
OSM	-.001	[-.003; .000]	Not rejected	-

*Bootstrapped Confidence Intervals

5.2.4.13 Hypothesis C1: Gender significantly moderates the relationship between technological propensity and productivity

Tests of moderation were conducted to assess the interactive moderating effect of gender and field of study (field). These tests were conducted on i) the relationship between technological propensity and productivity and ii) the relationship between HCI and productivity, respectively. These tests were conducted using Hayes' (2013) PROCESS plugin for SPSS. All tests of moderation were conducted with 5000 bootstrap iterations. In each test of moderation that follows, the independent variable is mean split into 'high' and 'low'.

For this test of moderation, PROCESS creates an interaction term, titled Int_1, which is the product of the standardised independent variable (technological propensity) and the moderator (gender). First, PROCESS checks the moderator (gender) (.903; p<.005), the independent variable (technological propensity) (.457; p<.151) and the interaction term (int_1) (.217; p<.727) as predictors of the dependent variable, productivity. In this case, the interaction term is not a significant predictor of the dependent variable. Gender is therefore not a significant mediator of the relationship between technological propensity and productivity. The null hypothesis is not rejected.

Next, PROCESS shows the difference between the categories of the moderating variable (male and female) on the relationship between technological propensity and productivity; in this case, male and female. These effects are plotted in Figure 20, below.

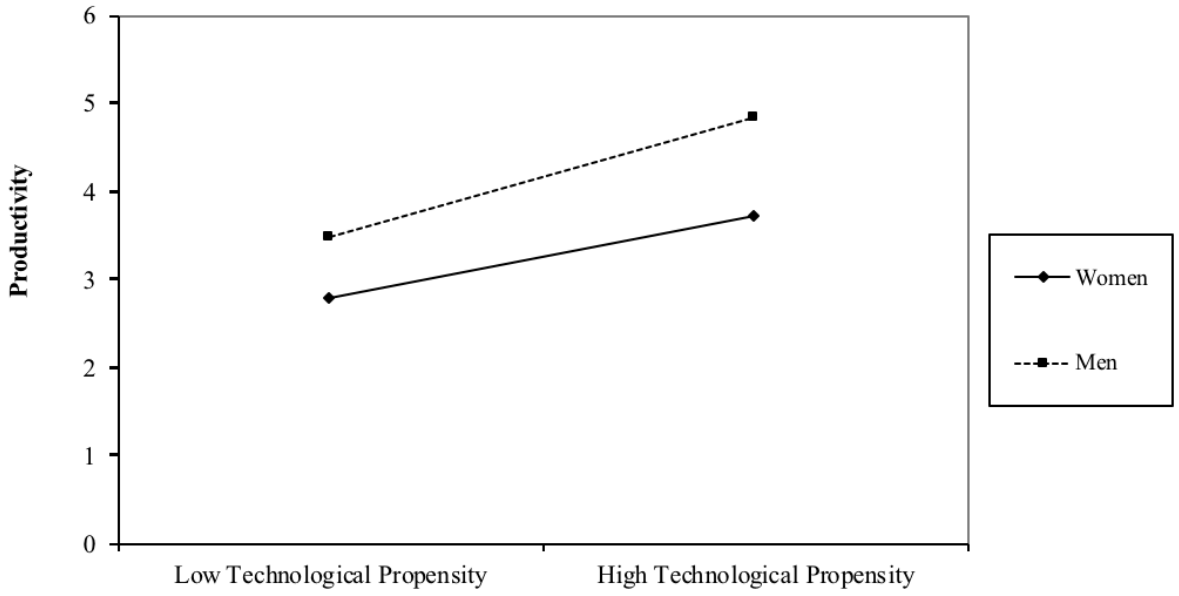


Figure 20: Hypothesis C1 (academic researcher sample) moderation plot

Examination of the interaction plot shows that men respondents seem to have higher rates of productivity at both high and low levels of technological propensity. The same applies for women respondents, but at a lower rate of productivity. According to the results of the analysis however, the difference in slopes is not significant.

5.2.4.14 Hypothesis C2: Field of Study significantly moderates the relationship between technological propensity and productivity

To test the moderating effect of field of study, each of the four fields of study were tested separately, as a moderator of the relationship between technological propensity and productivity. These include i) CLM (Commerce, Law and Management), ii) Sciences, iii) Humanities, and iv) Health. The results of these tests are reported in Table 56, below. Each interaction term is specific to the field of study of the hypothesis, in the form technological propensity multiplied by field of study. The moderation plots for each sub-hypothesis of Hypothesis C2 are represented in Figures 20 to 23, below.

5.2.4.14.1 Hypothesis C2.1 Field 1 (CLM) significantly moderates the relationship between technological propensity and productivity

The results of the moderation analysis show that the interaction term (technological propensity x Field1) is not a significant predictor of the outcome, productivity (-.126; p<.855). The null hypothesis is not rejected. These effects are plotted in Figure 21, below.

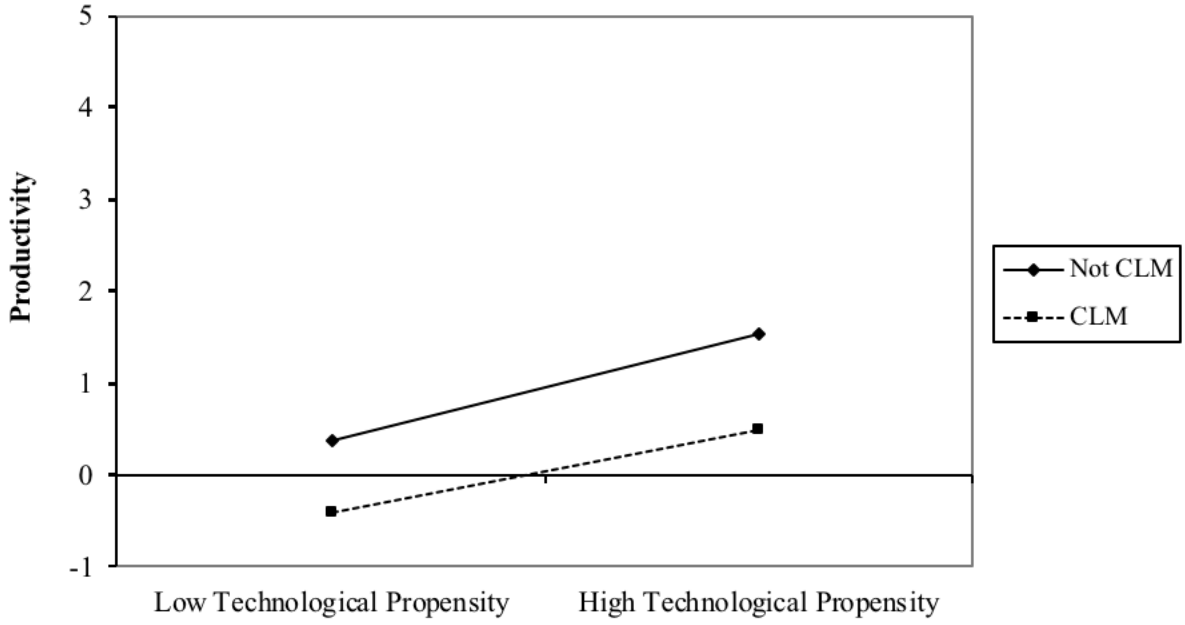


Figure 21: Hypothesis C2 (Field1: CLM) moderation plot

Examination of the interaction plot shows that respondents in Field 1 seem to have lower rates of productivity at both high and low levels of technological propensity. The same applies for respondents not in Field 1, but at slightly higher rates of productivity. According to the results of the analysis however, the difference in slopes is not significant.

5.2.4.14.2 Hypothesis C2.2 Field 2 (Sciences) significantly moderates the relationship between technological propensity and productivity

The results of the moderation analysis show that the interaction term (technological propensity x Field2) is not a significant predictor of the outcome, productivity (-.934; p<.193). The null hypothesis is not rejected. These effects are plotted in Figure 22, below.

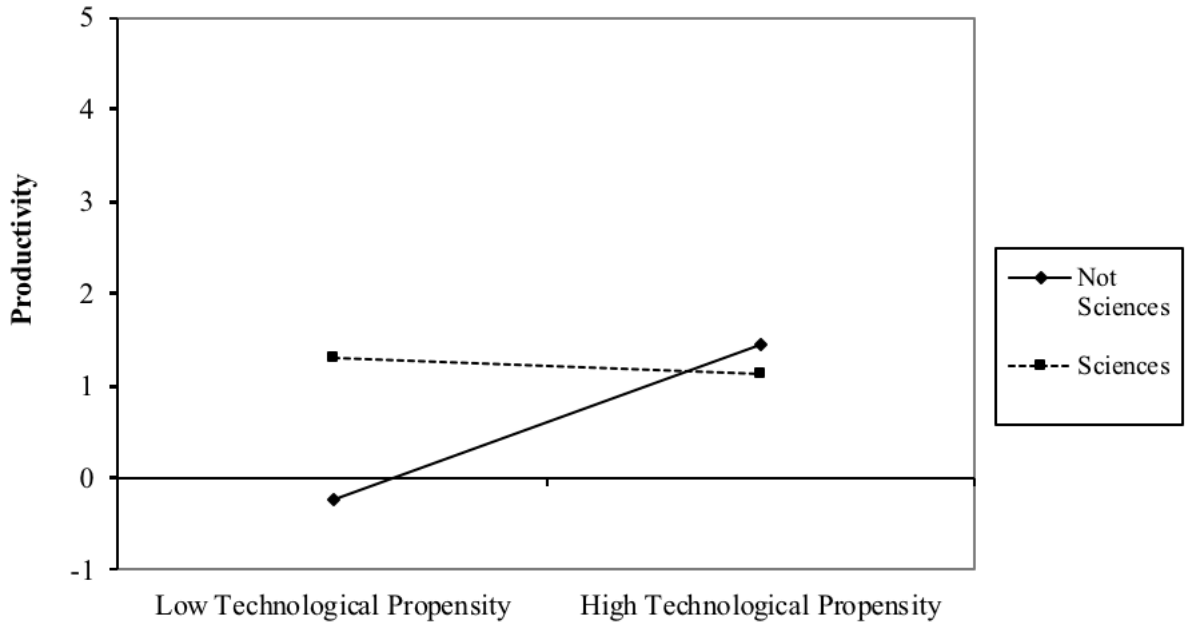


Figure 22: Hypothesis C2 (Field2: Sciences) moderation plot

Examination of the interaction plot shows that respondents in Field 2 seem to have higher rates of productivity at low levels of technological propensity, but lower levels of productivity at higher levels of technological propensity. The plot also shows that respondents not in Field 2 have lower rates of productivity at low levels of technological propensity, but higher rates of productivity at high levels of technological propensity. According to the results of the analysis however, the difference in slopes is not significant.

5.2.4.14.3 Hypothesis C2.3 Field 3 (Humanities) significantly moderates the relationship between technological propensity and productivity

The results of the moderation analysis show that the interaction term (technological propensity x Field3) is not a significant predictor of the outcome, productivity (-.370; p<.476). The null hypothesis is not rejected. These effects are plotted in Figure 23, below.

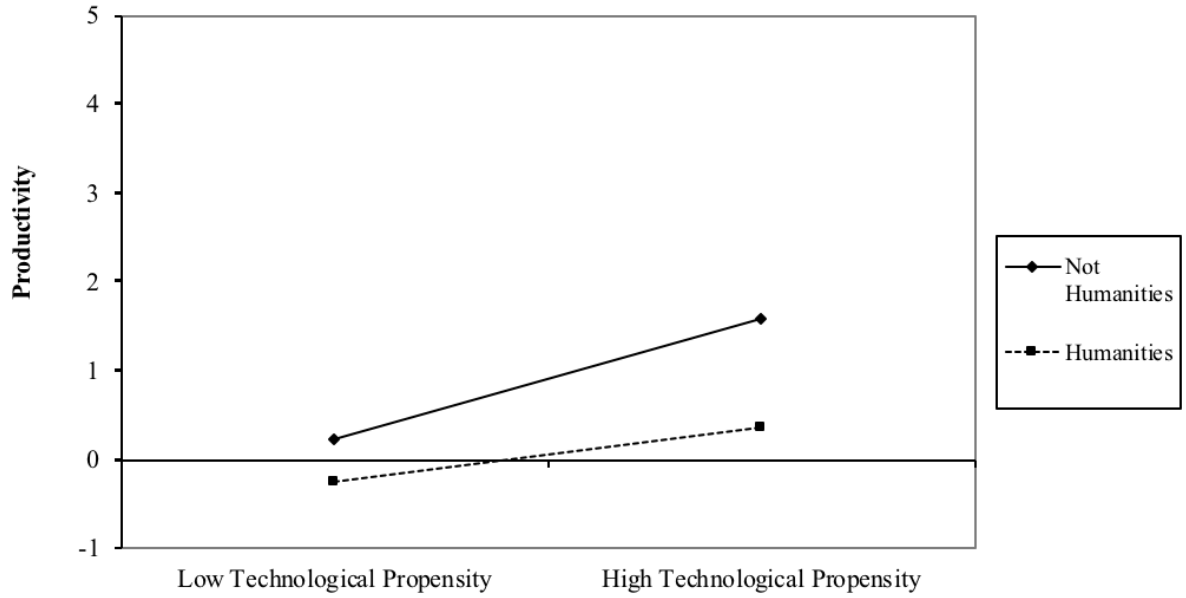


Figure 23: Hypothesis C2 (Field3: Humanities) moderation plot

Examination of the interaction plot shows that respondents in Field 3 seem to have lower rates of productivity at both high and low levels of technological propensity. The same applies for respondents not in Field 3, but at higher rates of productivity. According to the results of the analysis however, the difference in slopes is not significant.

5.2.4.14.4 Hypothesis C2.4 Field 4 (Health) significantly moderates the relationship between technological propensity and productivity

The results of the moderation analysis show that the interaction term (technological propensity x Field4) is not a significant predictor of the outcome, productivity (1.407; p<.154). The null hypothesis is not rejected. These effects are plotted in Figure 24, below.

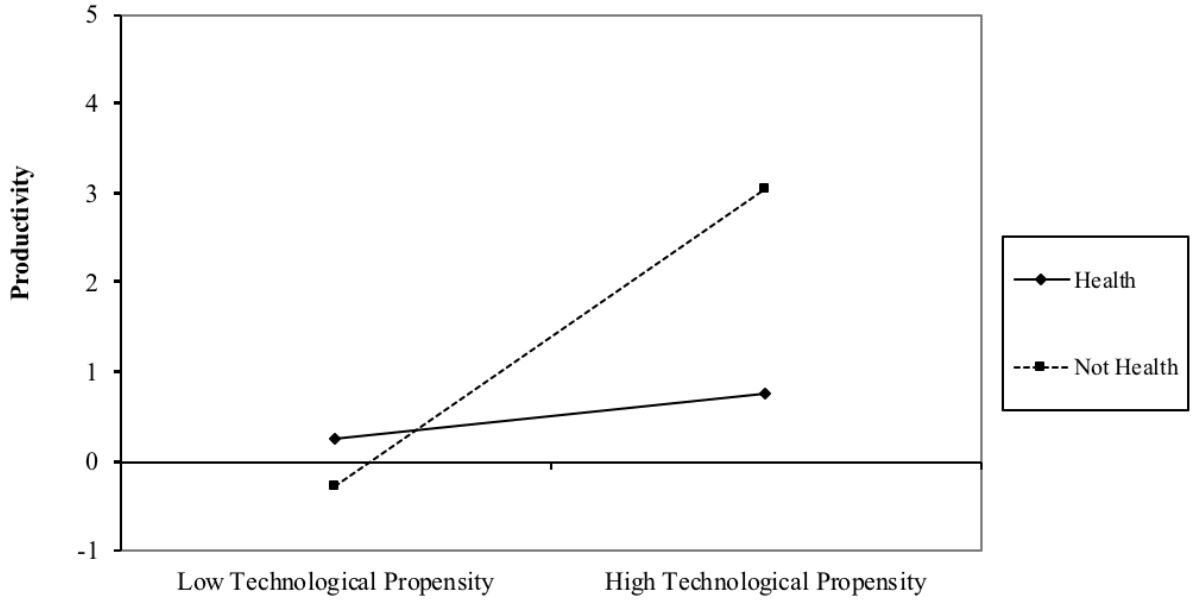


Figure 24: Hypothesis C2 (Field 4: Health) moderation plot

Examination of the interaction plot shows that respondents in Field 4 seem to have higher rates of productivity at low levels of technological propensity, but lower levels of productivity at high levels of technological propensity. The plot also shows that respondents not in Field 4 have lower rates of productivity at low levels of technological propensity, but higher rates of productivity at high levels of technological propensity. According to the results of the analysis however, the difference in slopes is not significant. Table 41 summarises the results of testing Hypothesis C2.

Table 41: Results of Moderation Testing for Hypothesis C2: Field of study moderates the relationship between technological propensity and productivity

Field of Study	Interaction (Technological Propensity x Field of Study)	Significance
Field1CLM	-.126; p<.855	Not significant
Field2Sciences	-.934; p<.193	Not significant
Field3Humanities	-.370; p<.476	Not significant
Field4Health	.1.407; p<.154	Not significant

Examination of the interaction plots above, shows that although there may be differences in the relationship between technological propensity and productivity by field of study, none of these differences are significant. Since field of study does not significantly moderate the

relationship between technological propensity and productivity, the null hypothesis is not rejected.

5.2.4.15 Hypothesis C3: Gender significantly moderates the relationship between Human Capital Investments (HCI) and productivity

The interaction term, int_1 (HCI x Gender) significantly predicts the outcome variable, productivity (.086; p<.001), indicating that that gender does moderate the relationship between HCI and productivity. Based on this result, the null hypothesis is rejected. The moderation plot for Hypothesis C3 is represented below in Figure 25.

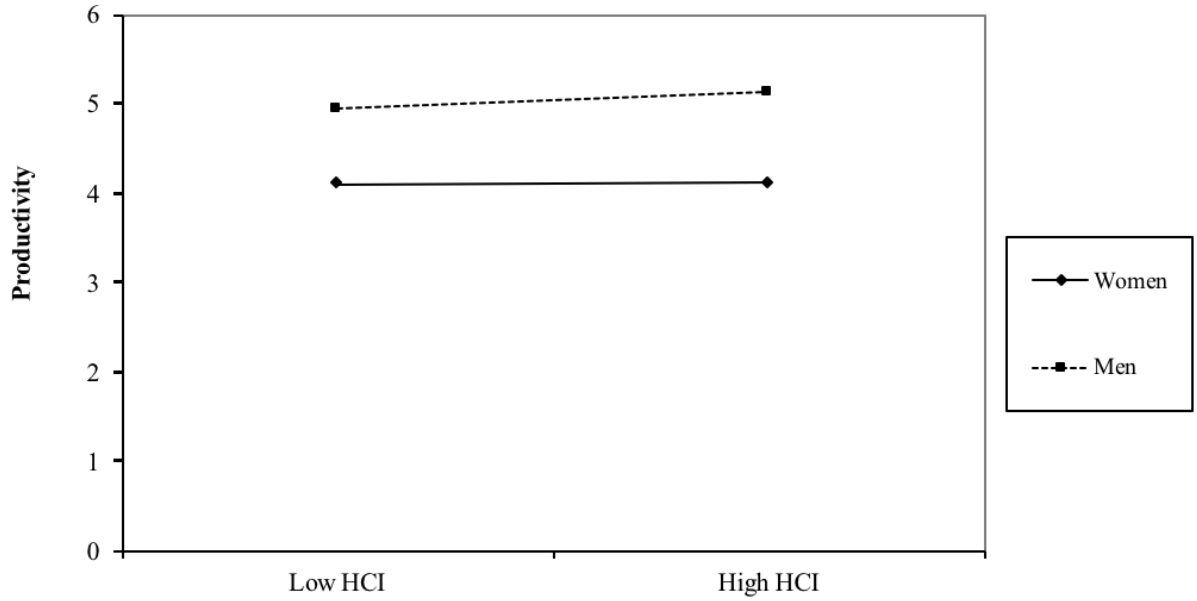


Figure 25: Hypothesis C3 (academic researcher sample) moderation plot

Examination of the interaction plots shows that that men respondents seem to have higher rates of productivity at low land high levels of HCI. The same applies for women respondents, but at lower rates of productivity. According to the results of the analysis, the difference in slopes is significant, meaning that men respondents may have a stronger relationship between HCI and productivity, than women respondents.

5.2.4.16 Hypothesis C4: Field of Study significantly moderates the relationship between HCI and productivity

To test the moderating effect of field of study, each of the four fields of study were tested separately, as a moderator of the relationship between HCI and productivity. Each interaction term is specific to the field of study of the hypothesis, in the form HCI multiplied by field of study. The moderation plots for each sub-hypothesis of Hypothesis C4 are represented in Figures 25 to 28, below.

5.2.4.16.1 Hypothesis C4.1: Field 1 (CLM) significantly moderates the relationship between Human Capital Investments (HCI) and productivity

The results of the moderation analysis show that the interaction term (HCI x Field1) is not a significant predictor of the outcome, productivity (0.001; p<.983). The null hypothesis is not rejected. These effects are plotted in Figure 26, below.

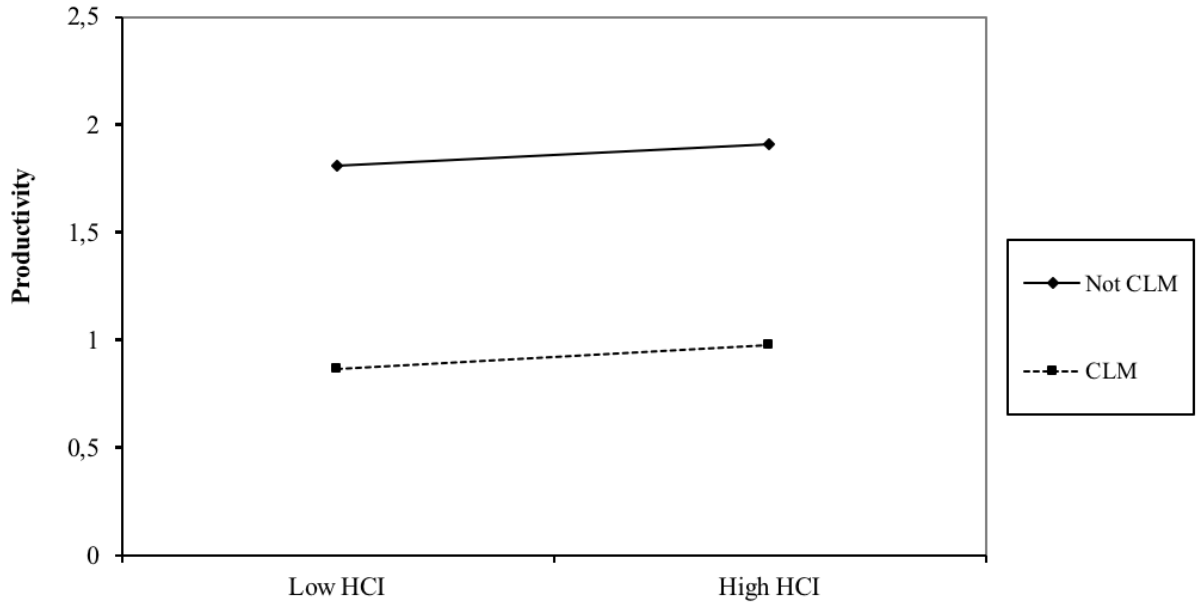


Figure 26: Hypothesis C4 (Field1: CLM) moderation plot

Examination of the interaction plot shows that respondents in Field 1 seem to have lower rates of productivity at both high and low levels of HCI. The same applies for respondents not in Field 1, but at a higher rate of productivity. According to the results of the analysis, the difference in slopes is not significant.

5.2.4.16.2 Hypothesis C4.2: Field 2 (Sciences) significantly moderates the relationship between Human Capital Investments (HCI) and productivity

The results of the moderation analysis show that the interaction term (HCI x Field2) is not a significant predictor of the outcome, productivity (-.039; p<.983). The null hypothesis is not rejected. These effects are plotted in Figure 27, below.

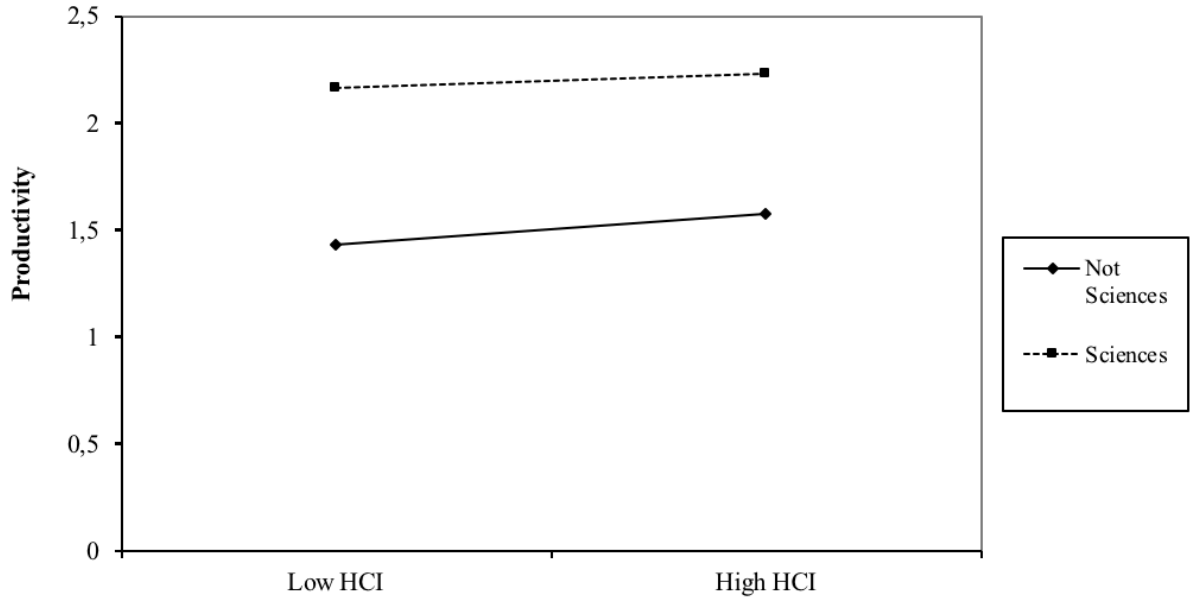


Figure 27: Hypothesis C4 (Field2: Sciences) moderation plot

Examination of the interaction plot shows that respondents in Field 2 seem to have higher rates of productivity at both high and low levels of HCI. The same applies for respondents not in Field 2, but at a lower rate of productivity. According to the results of the analysis, the difference in slopes is not significant.

5.2.4.16.3 Hypothesis C4.3: Field 3 (Humanities) significantly moderates the relationship between Human Capital Investments (HCI) and productivity

The results of the moderation analysis show that the interaction term (HCI x Field3) is not a significant predictor of the outcome, productivity (-.030; p<.409). The null hypothesis is not rejected. These effects are plotted in Figure 28, below.

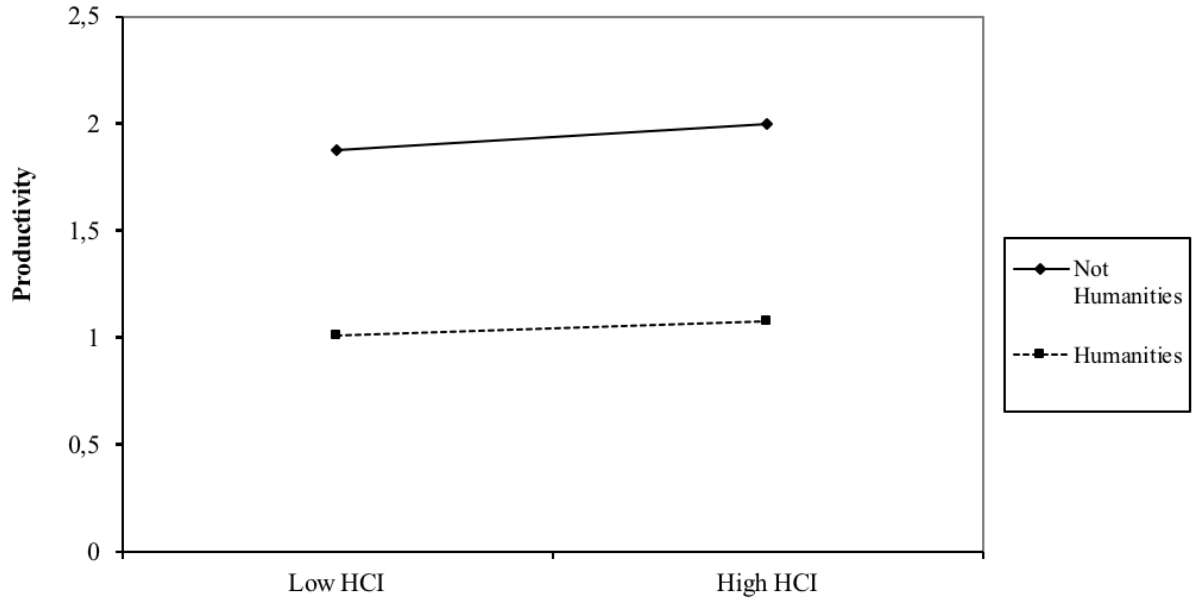


Figure 28: Hypothesis C4 (Field3: Humanities) moderation plot

Examination of the interaction plot shows that respondents in Field 3 seem to have lower rates of productivity at both high and low levels of HCI. The same applies for respondents not in Field 3, but at a higher rate of productivity. According to the results of the analysis, the difference in slopes is not significant.

5.2.4.16.4 Hypothesis C4.4: Field 4 (Health) significantly moderates the relationship between Human Capital Investments (HCI) and productivity

The results of the moderation analysis show that the interaction term (HCI x Field4) is not a significant predictor of the outcome, productivity (.036; p<.313). The null hypothesis is not rejected. These effects are plotted in Figure 29, below.

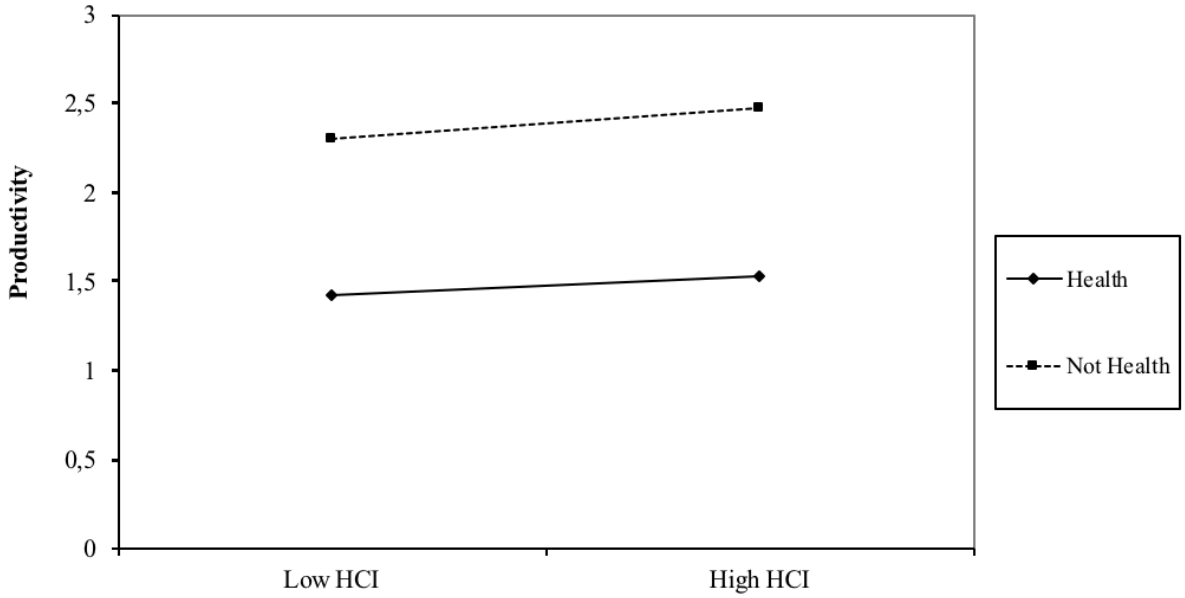


Figure 29: Hypothesis C4 (Field 4: Health) moderation plot

Examination of the interaction plot shows that respondents in Field 4 seem to have lower rates of productivity at both high and low levels of HCI. The same applies for respondents not in Field 4, but at a higher rate of productivity. According to the results of the analysis, the difference in slopes is not significant. The results of the tests of moderation for Hypothesis C4 are summarised in Table 42, below.

Table 42: Results of Moderation Testing for Hypothesis C4: Field of study moderates the relationship between HCI and productivity

Field of Study	Interaction (HCI x Field of Study)	Significance
Field1CLM	.001; p<.983	Not significant
Field2Sciences	-.039; p<.257	Not significant
Field3Humanities	-.030; p<.409	Not significant
Field4Health	.036; p<.313	Not significant

Examination of the interaction plots above, shows that although there may be differences in the relationship between HCI and productivity by field of study, none of these differences are significant. Since field of study does not significantly moderate the relationship between HCI and productivity, the null hypothesis is not rejected. The results of the tests of moderation for Hypothesis C are summarised in Table 43, below.

Table 43: Results of tests of moderation

Hypothesis	Moderating relationship	Null Hypothesis	Direction
C1	Gender moderates technological propensity-Productivity	Not rejected	-
C2	Field moderates technological propensity- productivity	Not rejected	-
C3	Gender moderates HCI- productivity	Rejected	-
C4	Field moderates HCI- productivity	Not rejected	-

This concludes the result of the academic researcher analysis. The results of all multivariate tests are summarised in Table 44, below. Thereafter, the results of the crowd-worker analysis are reported.

Table 44: Results of multivariate analyses (academic researcher sample)

Research Question A	What is the relationship between technological propensity and productivity?	Null Hypothesis
Hypothesis A1	Technological propensity is significantly associated with Productivity.	Not rejected
Hypothesis A2	Personality is significantly associated with technological propensity.	
Hypothesis A2.1	Openness to Experience is significantly associated with technological propensity	Rejected
Hypothesis A2.2	Extraversion is significantly associated with technological propensity	Not rejected
Hypothesis A2.3	Conscientiousness is significantly associated with technological propensity	Not rejected
Hypothesis A2.4	Agreeableness is significantly associated with technological propensity	Not rejected
Hypothesis A2.5	Neuroticism is significantly associated with technological propensity	Rejected
Hypothesis A3	Motivational Values are significantly associated with technological propensity	
Hypothesis A3.1	Self-Transcendence is significantly associated with technological propensity	Rejected
Hypothesis A3.2	Openness to Change is significantly associated with technological propensity	Rejected
Hypothesis A3.3	Conservation is significantly associated with technological propensity	Rejected
Hypothesis A3.4	Self-Enhancement is significantly associated with technological propensity	Not rejected
Hypothesis A4	Innovative Climate is significantly associated with technological propensity	
Hypothesis A4.1	Open Systems Models (OSM) are significantly associated with technological propensity	Not rejected

Hypothesis A4.2	Internal Process Models (IPM) are significantly associated with technological propensity	Not rejected
Hypothesis A6	Personality mediates the relationship between technological propensity and productivity.	
Hypothesis A6.1	Openness to Experience significantly mediates the relationship between technological propensity and productivity	Not rejected
Hypothesis A6.2	Extraversion significantly mediates the relationship between technological propensity and productivity	Not rejected
Hypothesis A6.3	Conscientiousness significantly mediates the relationship between technological propensity and productivity	Not rejected
Hypothesis A6.4	Agreeableness significantly mediates the relationship between technological propensity and productivity	Not rejected
Hypothesis A6.5	Neuroticism significantly mediates the relationship between technological propensity and productivity	Not rejected
Hypothesis A7	Motivational Values mediate the relationship between technological propensity and productivity.	
Hypothesis A7.1	Self-Transcendence significantly mediates the relationship between technological propensity and productivity.	Not rejected
Hypothesis A7.2	Openness to change significantly mediates the relationship between technological propensity and productivity.	Rejected
Hypothesis A7.3	Conservation significantly mediates the relationship between technological propensity and productivity.	Not rejected
Hypothesis A7.4	Self-Enhancement significantly mediates the relationship between technological propensity and productivity.	Not rejected
Hypothesis A8	Climate Perceptions mediates the relationship between technological propensity and Productivity.	
Hypothesis A8.1	Open Systems Models significantly mediate the relationship between technological propensity and productivity.	Not rejected
Hypothesis A8.2	Internal Process Models significantly mediate the relationship between technological propensity and productivity.	Not rejected
Hypothesis A9	Human Capital Investments (HCI) mediates the relationship between technological propensity and productivity.	Not rejected
Research Question B	What is the relationship between Human Capital Investments (HCI) and productivity?	
Hypothesis B1	Human Capital Investments (HCI) are significantly associated with productivity.	Rejected
Hypothesis B2	Personality mediates the relationship between Human Capital Investments (HCI) and productivity.	
Hypothesis B2.1	Openness to Experience significantly mediates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis B2.2	Extraversion significantly mediates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis B2.3	Conscientiousness significantly mediates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis B2.4	Agreeableness significantly mediates the relationship between Human Capital Investments (HCI) and productivity	Not rejected

Hypothesis B2.5	Neuroticism significantly mediates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis B3	Motivational Values mediate the relationship between Human Capital Investments (HCI) and productivity.	
Hypothesis B3.1	Self-Transcendence mediates the relationship between Human Capital Investments (HCI) and productivity.	Not rejected
Hypothesis B3.2	Openness to Change mediates the relationship between Human Capital Investments (HCI) and productivity.	Not rejected
Hypothesis B3.3	Conservation mediates the relationship between Human Capital Investments (HCI) and productivity.	Not rejected
Hypothesis B3.4	Self-Enhancement mediates the relationship between Human Capital Investments (HCI) and productivity.	Not rejected
Hypothesis B4	Climate Perceptions mediates the relationship between Human Capital Investments (HCI) and productivity.	
Hypothesis B4.1	Open Systems Models mediate the relationship between Human Capital Investments (HCI) and productivity.	Not rejected
Hypothesis B4.2	Internal Process Models (OSM) mediates the relationship between Human Capital Investments (HCI) and productivity.	Not rejected
Research Question C	What are the interactive effects of gender and field of study on the relationships between technological propensity, Human Capital Investments (HCI) and productivity?	
Hypothesis C1	Gender significantly moderates the relationship between technological propensity and productivity	Not rejected
Hypothesis C2	Field of Study significantly moderates the relationship between technological propensity and productivity	Rejected
Hypothesis C3	Gender significantly moderates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis C4	Field of Study significantly moderates the relationship between Human Capital Investments (HCI) and productivity.	Not rejected

Having concluded the academic sample analysis, the crowd-worker analysis follows.

5.3 SECTION B: CROWD-WORKER SAMPLE ANALYSIS

The statistical tests conducted on data gathered from the crowd-worker sample are now reported. Firstly, a discussion of univariate descriptive is provided. Thereafter, the results of the tests of bivariate correlations follow. Results of EFAs for the crowd-worker analysis are also reported. Finally, a discussion of the hypotheses, each tested by way of multiple hierarchical regressions, mediations and moderations follows. The results of the tests of univariate descriptives of the crowd-worker sample are now provided and discussed.

5.3.1 Univariate results: Measures, Location, Central Tendency and Statistical Dispersion

The same procedure followed for the academic researcher sample (Section A) was followed for the crowd-worker sample. Results are summarised in tables, as follows.

5.3.1.1 Descriptive statistics

In this section, the univariate descriptive statistics for biographical variables are reported. These include age, gender, education, years of experience, nationality, language, marital status, profession, industry and number of dependent children. These statistics are reported in table 45, below.

Table 45: Descriptive statistics: Crowd worker sample

Variable	Mean	Standard Deviation	Variance	Skewness	Kurtosis
Age	35.15	11.092	123.040	1.167	.941
Number of HIT's on MTurk	19406.59	62033.321	3.848	6.577	56.056
Years on MTurk	3.138	13.180	173.722	17.054	306.159
Gender (1=male)	59.2%	-	-	-	-
Nationality1 (1=USA)	59.4%	-	-	-	-
Nationality2 (1 = India)	32.2%	-	-	-	-
Nationality3 (1=Other)	8.4%	-	-	-	-
Language1 (1 = English)	75.4%	-	-	-	-
Language2 (1 = Tamil)	7.7%	-	-	-	-
Language3 (1 = Other)	16.9%	-	-	-	-
Marital status (1=yes)	56.1%	-	-	-	-
Children	.90	1.019	1.039	1.045	.993
Profession (1=S&T)	26.0%	-	-	-	-
Industry (1=S&T)	28.8%	-	-	-	-
Education 1 (1=Primary School)	.2%	-	-	-	-
Education 2 (1= High School)	11.2%	-	-	-	-
Education 3(1= U/H)	54.3%	-	-	-	-
Education 4 (1=Masters)	30.1%	-	-	-	-
Education 5 (1=PhD)	3.3%	-	-	-	-

*means of binary variables are instead reported as percentages. Abbreviations: S&T = science and technology, U/H = Undergraduate/Honours

5.3.1.2 Crowd-Worker Productivity (CWP)

Crowd-worker productivity (CWP) was measured by a ratio, which divided 'number of MTurk HITs completed' over the total number of years of experience as an MTurk crowd worker. Although estimates vary, it is estimated that most MTurk HIT's take an average of 10 to 15 minutes to complete (Goodman, et al., 2013). It is assumed that these tend towards an average over a large sample.

Table 46: Crowd-Worker Productivity (CWP)

Variable	Mean	Standard Deviation	Variance	Skewness	Kurtosis
Total HITs	19406.59	62033.321	3.848	6.577	56.056
Years on MTurk	3.138	13.180	173.722	17.054	306.159
CWP	6854.891	18130.329	328708856	6.655	59.861

5.3.1.3 Scale measures

Descriptive statistics pertaining to personality, motivational values and technological propensity are now presented in Table 47, below. Collectively, these are referred to as HRM determinants of CWP.

Table 47: HRM determinants of CWP

Variable		Mean	Median	Std. Deviation	Variance
Personality					
	Agreeableness	5.159	5.200	1.058	1.120
	Extraversion	4.274	4.400	1.319	1.741
	Conscientiousness	5.280	5.400	.975	.952
	Openness to experience	4.976	5.000	1.035	1.072
	Neuroticism	3.372	3.400	1.187	1.411
Motivational Values					
	Self-transcendence	4.462	4.750	1.087	1.183
	Openness to change	4.048	4.000	.919	.846
	Conservation	4.071	4.166	1.013	1.028
	Self-enhancement	3.867	4.000	1.001	1.002
Technological Propensity					

Variable		Mean	Median	Std. Deviation	Variance
	Technological use	2.891	3.000	.552	.305
	Crowd propensity	3.163	3.250	.581	.338
	Open orientation	3.030	3.000	.513	.264
	Collaborative propensity	3.130	3.250	.529	.280
	Tolerance for disruption	3.463	3.500	.536	.288
	Technological propensity (Ave)	3.135	3.150	.338	.15

Results reported in the table above are discussed in the proceeding sections. As previously, the results of the process of statistical testing are given in the following sections under the heading that represents each hypothesis tested.

5.3.2 Bivariate correlations

The same procedure that was used to test for bivariate correlation that was used in Section A (the academic research sample) is used here. Tests for correlation are not used to test hypotheses. However, this section is also structured according to hypotheses, for ease of reporting.

5.3.2.1 Technological Propensity and CWP

The correlations between technological propensity and CWP are summarised in Table 48, below.

Table 48: Correlations between technological propensity and CWP

Technological propensity	MTurk Years	MTurk HITs	CWP
Tolerance for Disruption	.107*	-	-
Technological Propensity	-	.086*	-
Crowd Propensity	.110*	-	-
Open Orientation	-	-	-
Collaborative Propensity	-	-	-.087*
Technological propensity (Ave)	.091*	-	-

*significant at the 0.01 level (2-tailed)

Technological propensity is found to not be significantly correlated with CWP.

5.3.2.2 Personality and Technological Propensity

The tests of correlation between personality and technological propensity are summarised in Table 49, below.

Table 49: Correlations between personality and technological propensity

Technological propensity	Openness to experience	Neuroticism	Conscientious-ness	Agreeable-ness	Extraversion
Tolerance for Disruption	.257**	-.273**	.230**	.307**	.354*
Technological Propensity	.129**	-.121**	-	-	.113*
Crowd Propensity	.295**	-	-	.147**	.247**
Open Orientation	.174**	-	-	.098*	.165**
Collaborative Propensity	.193**	-.176**	.085*	.304**	.446**
Technological propensity (Ave)	.347**	-.156**	-	.295**	.424**

*significant at the 0.01 level (2-tailed)

** - significant at the 0.05 level (1-tailed)

Openness to experience, neuroticism, agreeableness and extraversion were all found to be significantly correlated with the average technological propensity score. Only conscientiousness was found to not be significantly correlated with the technological propensity score.

5.3.2.3 Motivational Values and Technological Propensity

The tests of correlation between motivational values and technological propensity are summarised in Table 50, below.

Table 50: Correlations between motivational values and technological propensity

Technological propensity	Self-Transcendence	Openness to Change	Conservation	Self-Enhancement
Tolerance for Disruption	.231**	.338**	.312**	.284**
Technological Propensity	-	.130**	-	.122**
Crowd Propensity	.140**	.181**	-	.143**
Open Orientation	.132**	.172**	-	.149**
Collaborative Propensity	.280**	.256**	.187**	.223**

Technological propensity (Ave)	.261**	.353**	.165**	.316**

** - significant at the 0.05 level (1-tailed)

All four of the Schwartz' (1992) higher-order values of motivation were found to be significantly correlated with technological propensity.

5.3.2.4 HCI and Technological Propensity

The tests of correlation between HCI and technological propensity are summarised in Table 51, below.

Table 51: Correlations between HCI and technological propensity

Technological propensity	Years on MTurk	Education
Tolerance for Disruption	.107*	.197**
Technological Propensity	-	-
Crowd propensity	.110**	.138**
Open orientation	-	-
Collaborative Propensity	-	.179**
Technological propensity (Ave)	.091*	.191**

*significant at the 0.01 level (2-tailed)

** - significant at the 0.05 level (1-tailed)

HCI (measured by years of experience as an MTurker) are found to be significantly correlated with technological propensity.

5.3.2.5 HCI and CWP

The test of bivariate correlation between HCI and CWP is summarised in Table 52, below.

Table 52: Correlations between HCI and CWP

HCI	MTurk Years	MTurk HITs	CWP
Education	.096*	.099*	-

*significant at the 0.01 level (2-tailed)

There is no significant correlation between HCI (years of experience as an MTurker) and CWP. EFAs were conducted to test for discriminant and convergent validity. The results of these analyses, for the crowd-worker sample, are reported next.

5.3.3 Tests of Discriminant and Convergent Validity

Exploratory Factor Analyses (EFAs) were conducted to test for discriminant and convergent validity (Campbell & Fisk, 1959), of the TIPI, PVQ and technological propensity scales respectively. Given that crowd-workers tend to work from home (Goodman, et al., 2013), crowd-workers' work climate perceptions were not investigated. Field (2012) suggests that a sample size over 300 is generally considered adequate for a Factor Analysis. Exploratory Factor Analysis was conducted to identify correlations between observations that stem from their relationship to latent variables in the data, each of which takes the form of a linear model (Field, 2012). Prior to each EFA, a process of data screening was conducted, to detect any problematic inter-correlation between variables and issues relating to singularity (Field, 2012). The respective details of the data screening and subsequent exploratory factor analyses performed on the TIPI, PVQ, OCM and technological propensity scales now follow.

5.3.3.1 Personality (The Modified TIPI scale)

The correlation matrix produced a determinant of 5.5 ($p>0.0001$), indicating that multi-collinearity was not a threat to interpretation. KMO=.897, indicating high sampling adequacy and Bartlett's test of sphericity produced a significant result ($p=.000$, $<.05$). Prior to extraction, 25 linear components were identified, correlating with the 25 items of the modified TIPI scale. Following extraction, no items were found be associated with extraction communalities. Principal axis factoring, using orthogonal rotate on (Varimax rotation with Kaiser normalisation), produced 6 latent factors with a cumulative variance of 56.699%, confirmed by an accompanying Scree plot.

5.3.3.2 Motivational values (The PVQ)

The correlation matrix produced a determinant of 1.93, indicating that multicollinearity between scale items was not a threat to interpretation. KMO=.930 indicating sample adequacy and Bartlett's test was significant ($p=0.000$). Before extraction, 21 linear components were

discovered, following extraction, only 1 item (Hedonism1) had extraction communalities. Principal axis factoring, using Varimax rotation with Kaiser normalisation produced a rotated factor matrix with three latent constructs (as per the accompanying Scree plot), with a cumulative variance of 52.485%.

5.3.3.3 Technological Propensity (The Technological Propensity Scale)

The correlation matrix provided a determinant of 0.17 (p.0.0001), with a KMO value of .805 and a significant result for Bartlett's test of sphericity. Following extraction, no items were found to have extraction communalities. Principal axis factoring using Varimax rotation with Kaiser normalisation produced five latent factors with a cumulative variance of 51.360%. Results of multivariate testing for the academic researcher sample are now reported, as follows.

5.3.4 Multivariate Analysis: Regression, Mediation and Moderation Analysis

Regression covariates were chosen on the basis of theory. EFAs were conducted to test for singularity and potential multicollinearity of regression covariates. In all regression models, VIF values were below 10 and Tolerance values were above .20, indicating that multi-collinearity was not to be taken as a threat to interpretation (Field, 2012). All tests of regression, mediation and moderation were bootstrapped. Table 53 below, provides a list of covariates that were chosen for inclusion in regression models, for the crowd-worker researcher sample.

Table 53: Covariate selection for crowd-worker sample

Covariate Code*	Covariate name	Description
Age	Age	The age of the respondents, in years
Gender	Gender	Gender of respondents with 1 representing males and 0 representing females
Nat1USA	Nationality (American)	Respondents that are from the USA
Nat3Other	Nationality (not American, nor Indian)	Respondents that were not from the USA, nor from India
Lan1English	Language (English)	Respondents that spoke English as a first language

Covariate Code*	Covariate name	Description
Children	Number of dependent children	The number of dependent children supported in the respondent's family
Profession	Profession	Profession was made binary – those respondents whose professions were of a scientific and/or technological nature (1) and those whose professions were not (0).
Education	Education	A measurement of the respondents' level of education on a scale of 1 to 5, with 1 representing primary school, 2 representing high school, 3 representing undergraduate/honours level education, 4 representing Masters level education and 5 representing PhD level education.

* For ease of reporting, abbreviated covariate codes (listed in the first column) are used for equations and specifications henceforth.

Tests of regression, mediation and moderation were conducted for data collected from the crowd-worker sample. The results of these tests are reported below. This section is structured according to the hypotheses.

5.3.4.1 Hypothesis A1: Technological propensity is significantly associated with Crowd-Worker Productivity (CWP).

This hypothesis was tested by a hierarchical multiple regression. In the first model, covariates account for 4.4% of total variance (R^2 = .044; p<.004) in the model. The inclusion of the independent variable, technological propensity accounts for no further significant variance (R^2 = .044; p<.964). The specification is represented in the equation provided, as follows:

Y(TCWP) = 6.422 +.027(Age) -.089(Gender) -.089(Nat1USA) -.880(Nat3Other) -.247(Lan1Eng) -.133(Children) -.304(Profession) + .109(Education) +.013(technological propensity)

As standardised coefficients, only Age (.147; p<.002) and Nat3Other (-.117; p<.015) are significant. The independent variable, technological propensity (.002; p<.964), is not significant. Based on this analysis, the null hypothesis is not rejected. Technological propensity is not significantly associated with CWP.

5.3.4.2 Hypothesis A2: Personality is significantly associated with technological propensity

As for the previous academic researcher sample, this hypothesis was tested by testing the association of each of the Big Five Personality traits with technological propensity, including openness to experience, extraversion, conscientiousness, neuroticism and agreeableness, as follows.

5.3.4.2.1 Hypothesis A2.1: Openness to experience is significantly associated with technological propensity

In Model 1, covariate predictors account for 13.2% of variance in the mode (R2 = .132; p<.000). The inclusion of Openness to Experience (PersO) as an independent variable (R^2 = .229; p<.000) in the model accounts for an additional 9.7% of variance in the model (R^2 Change = .097). The specification is represented as follows:

> Y(T6GProp) = 1.011 -.002(Age) -.003(Gender) -.065(Nat1USA) -.043(Nat3Other) +.014Lan1Eng +.010 (Children) -.006(Profession) +.012(Education) +.034(Openness to Experience)

Significant standardised coefficients include Nat1USA (-.285; p<.000), Nat3Other (-.108; p<.009), Children (.095; p<.015) and the independent variable PersO (.316; p<.000). Based on this result, the null hypothesis is rejected. Openness to experience is significantly associated with technological propensity.

5.3.4.2.2 Hypothesis A2.2: Extraversion is significantly associated with technological propensity

Selected covariates account for a total of 13.2% of variance in the model (R^2 =.132; p<.000). The inclusion of the independent variable, Extraversion (PersE) accounts for a further 12.8% (R^2 Change = .1278. The specification is provided as follows:

Y(T6GProp) = 1.031 -.002(Age) +.003(Gender) -.043(Nat1USA) -.028(Nat3Other) +.006 (Lan1Eng) +.003 (Children) -.004(Profession) + .014(Education) +.032(Extraversion)

Significant standardised coefficients include Age (-.153; p<.000), Nat1USA (-.189; p<.001), Education (.087; p<.024) and the independent variable, PersE (.375; p<.000). The null hypothesis is rejected. Extraversion is significantly associated with technological propensity.

5.3.4.2.3 Hypothesis A2.3: Conscientiousness is significantly associated with technological propensity

The inclusion of covariates accounts for 13.2% of total variance in the model. Conscientiousness (PersC) (R^2 =.146; p<.002), as an independent variable, accounts for an additional 1.5% of significant variance (R^2 =.015). The specification is expressed as the equation:

Y(T6GProp) = 1.100 -.002(Age) -.001(Gender) -.071(Nat1USA) -.044(Nat3Other) +.013(Lang1Eng) +.008 (Children) -.005(Profession) +.017 (Education) +.015(Conscientiousness)

Significant standardised coefficients include Age (-.181; p<.000), Nat1USA (-.315; p<.000), Nat3Other (-.112; p<.0.011) and education (.108; p<.009) as well as PersC (.128; p<.002). The null hypothesis is rejected. Conscientiousness is significantly associated with technological propensity

5.3.4.2.4 Hypothesis A2.4: Neuroticism is significantly associated with technological propensity

In Model 2, the inclusion of Neuroticism (PersN) (R^2 = .186; p<.000) accounts for an additional 5.4% of total model variance (R^2 change = .054), over the initial 13.2% of variance accounted by regression covariates. The specification is represented in the equation below:

Y(T6GProp) = 1.265 -.002(Age) -.011(Gender) -.070(Nat1USA) -.035(Nat3Other) +.014(Lan1Eng) +.008 (Children) -.005(Profession) + .017(Education) -.023 (Neuroticism)

Significant standardised coefficients include Age (-.202; p<.000), NatUSA (-.311; p<.000), Nat3Other (-.087; p<.042) and education (.106; p<.009) as well as PersN (-.244; p<.000). The null hypothesis is rejected. Neuroticism is negatively and significantly associated with technological propensity.

5.3.4.2.5 Hypothesis A2.5: Agreeableness is significantly associated with technological propensity

In Model 2, the inclusion of the independent variable Agreeableness (PersA) (R^2 =.246; p<.000) accounts for an additional 11.5% of variance in the total regression model (R^2 change = .115), over the 13.2% contributed by covariates. The specification is represented as follows:

Y(T6GProp) = .982 -.002(Age) +.006(Gender) -.050(Nat1USA) -.027(Nat3Other) +.007(Lan1Eng) +.007 (Children) -.004(Profession) + .018(Education) +.037(Agreeableness)

Significant standardised coefficients include Age (-.229; p<.000), Nat1USA (-.221; p<.000), education (.117; p<.003) and PersA (.353; p<.000). The null hypothesis is rejected. Agreeableness is positively and significantly associated with technological propensity.

Table 54: Results of Regressions for Hypothesis A2: Personality is significantly associated with technological propensity

Personality	R^2 (Model 1)	R^2 (Model 2)	R^2 Change	Null hypothesis	Direction
Openness to experience	.132; p<.000	.229; p<.000)	.097	Rejected	Positive (.316; p<.000)
Extraversion	.132; p<.000	.260; p<.000)	.128	Rejected	Positive (.375; p<.000
Conscientiousness	.132; p<.000	.146 p<.039)	.015	Rejected	Positive.128; p<.002)

Personality	R^2 (Model 1)	R^2 (Model 2)	R^2 Change	Null hypothesis	Direction
Neuroticism	.132; p<.000	.186; p<.000)	.054	Rejected	Negative (-.244; p<.000)
Agreeableness	.132; p<.000	.246; p<.000)	.115	Rejected	Positive (.353; p<.000)

5.3.4.3 Hypothesis A3: Motivational Values are significantly associated with technological propensity

A test of regression was conducted to assess the relationship between motivational values and technological propensity. Each of the 4 higher order values (Schwartz, 2012) of motivation was tested for association with technological propensity, as follows.

5.3.4.3.1 Hypothesis A3.1: Self-Transcendence is significantly associated with technological propensity

In Model 1, covariates account for a total of 13.2% of variance in the regression model (R^2 = .132; p<.000). In Model 2, following inclusion of the independent variable, self-transcendence (MotST) (R^2 = .183; p<.000), accounts for a further 5.2% of total variance (R^2 change = .052). The specification is represented as follows:

Y(T6GProp) = 1.063 -.002(Age) +.002(Gender) -.069(Nat1USA) -.048(Nat3Other) +.012(Lan1Eng) +.008 (Children) -.004(Profession) + .017(Education) +.023 (MotST)

Significant standardised coefficients include Age (-.159; p<.000), NatUSA (-.305; p<.000), Nat3Other (-.121; p<.005), Education (.107; p<.008) as well as MotST (.228; p<.000). The null hypothesis is rejected. Self-transcendence is significantly associated with technological propensity.

5.3.4.3.2 Hypothesis A3.2: Openness to Change is significantly associated with technological propensity

In Model 2, the inclusion of the independent variable openness to change (MotOC) (R^2 = .201; p<.000), accounts for a further 6.9% of total variance in the regression model (R^2 change = .069). The specification is provided as follows:

> Y(T6GProp) = 1.258 -.001(Age) +.003(Gender) -.066(Nat1USA) -.047(Nat3Other) +.013(Lan1Eng) +.007 (Children) -.004(Profession) + .014(Education) +.032(MotOC)

Significant standardised coefficients include Age (-.132; p<.001), Nat1USA (-.293; p<.000), Nat3Other (-.119; p<.005), education (.090; p<.024) and MotOC (.265; p<.000). The null hypothesis is rejected. Openness to change is significantly associated with technological propensity.

5.3.4.3.3 Hypothesis A3.3: Conservation is significantly associated with technological propensity

The inclusion of the independent variable, conservation (MotC) (R^2 = .144; p<.006) accounts for a further 1.2% of significant variance in the model (R^2 change = .012). The specification is provided below.

> Y(T6GProp) = 1.117 -.002(Age) +.001(Gender) -.066(Nat1USA) -.043(Nat3Other) +.013(Lan1Eng) +.006 (Children) -.004(Profession) + .016(Education) +.012(MotC)

Significant standardised coefficients include Age (-.158; p<.000), Nat1USA (-.293; p<.000), Nat3Other (-.108; p<.013), education (.105; p<.011) and MotC (.112; p<.006). The null hypothesis is rejected. Conservation is significantly associated with technological propensity.

5.3.4.3.4 Hypothesis A3.4: Self-Enhancement is significantly associated with technological propensity

In Model 2, the inclusion of the independent variable, self-enhancement (MotSE) (R^2 = .194; p<.000) accounts for an additional 6.2% of significant variance in the model (R^2 change = .062). The specification is as follows:

Y(T6GProp) = 1.239 -.001(Age) +.001(Gender) -.062(Nat1USA) -.048(Nat3Other) +.011(Lan1Eng) +.006 (Children) -.005(Profession) + .014(Education) +.025(MotSE)

Significant standardised coefficients include Age (-.110; p<.007), Nat1USA (-.275; p<-.000), Nat3Other (-.120; p<.005), education (.087; p<.030) and MotSE (.255; p<.000). The null hypothesis is rejected. Self-enhancement is significantly associated with technological propensity.

Table 55: Results of Regressions for Hypothesis A3: Motivational values are significantly associated with technological propensity

Motivational Values	R^2 (Model 1)	R^2 (Model 2)	R^2 Change	Null Hypothesis	Direction
Self-Transcendence	.132; p=.000	.183; p=.000	.052	Rejected	Positive (.228; p<.000)
Openness to Change	.132; p=.000	.201; p=.000	.069	Rejected	Positive (.265; p<.000)
Conservation	.132; p=.000	.144; p=.009	.012	Rejected	Positive (.112; p<.006)
Self-Enhancement	.132; p=.000	.194; p=.000	.062	Rejected	Positive (.255; p<.000)

5.3.4.4 Hypothesis A5: Personality mediates the relationship between technological propensity and Crowd-Worker Research Productivity (CWP).

Each of the Big Five Personality traits were tested for their mediating effect on the relationship between CWP and technological propensity. Bootstrapping was performed for each of these tests. The results of each hypothesis test are reported, as follows.

5.3.4.4.1 Hypothesis A5.1: Openness to Experience mediates the relationship between technological propensity and Crowd-Worker Productivity (CWP)

Technological propensity (1.108; p<.000) does predict openness to experience (PersO). Significant covariate predictors include Age (.010; p<.026) and number of children (-.114; p<.010). PersO (.135; p<.138) does not predict the dependent variable CWP, nor does technological propensity (-.136; p<.618). Significant covariates include Age (.026; p<.001) and Nat3Other (-.888; p<.009). The mediating effect of PersO (.150) is not significant since BootCI [-.042; .363]. The null hypothesis is not rejected. Openness to experience does not mediate the relationship between technological propensity and CWP.

5.3.4.4.2 Hypothesis 5A.2: Extraversion significantly mediates the relationship between technological propensity and CWP

Technological propensity (1.620; p<.000) does predict extraversion (PersE). Significant covariates include only Nat1USA (-.428; p<.018). Pers E (-.128; p<.080) does not predict CWP. Technological propensity (.220; p<.415) does not predict CWP. Significant covariates include only Age (.028; p<.000) and Nat3Other (-.923; p<.007). The mediating effect of PersE (-.207) is not significant, since BootCI [-.464; .016]. Based on this result, the null hypothesis is not rejected. Extraversion does not mediate the relationship between technological propensity and CWP.

5.3.4.4.3 Hypothesis A5.3: Conscientiousness' significantly mediates the relationship between technological propensity and CWP

Technological propensity (.469; p<.001) does predict conscientiousness (PersC), as does the covariate Age (.025; p<.000). PersC (.178; p<.083) does not predict CWP nor does technological propensity (-.070; p<.783). Significant covariates include Age (.023; p<.004) and Nat3Other (-.898; p<.009). The mediating effect of PerC (.084) is significant, since BootCI [.001; .230]. Therefore, the null hypothesis is rejected. Conscientiousness does mediate the relationship between technological propensity and CWP.

5.3.4.4.4 Hypothesis A5.4: Neuroticism significantly mediates the relationship between technological propensity and CWP

Technological propensity (-1.026; p<.000) does predict neuroticism (PersN), as do the covariates Age (-.028; p<.000), Gender (-.412; p<.000) and Nat1USA (-.235; p<.000). PersN (-.143; p<.103) does not predict CWP, nor does technological propensity (-.133; p=<609). Both Age (.023; p<.004) and Nat3Other (-.836; p<.015) are significant covariate predictors of CWP. The mediating effect of PersN (.147) is not significant since BootCI [-.017; .363]. Based on the result of this analysis, the null hypothesis is not rejected. Neuroticism does not mediate the relationship between technological propensity and CWP.

5.3.4.4.5 Hypothesis A5.5: Agreeableness significantly mediates the relationship between technological propensity and CWP

Technological propensity (1.313; p<.000) does predict agreeableness (PersA), as do the covariates Age (.029; p<.000), Gender (-.183; p<.041) and Nat3Other (-.305; p=<037). PersA (.108; p<.286) does not predict CWP, nor does technological propensity (-.128; p<.644). Of the predictor covariates in the model, both Age (.024; p<.003) and Nat3Other (-.847; p<.015) are significant predictors of CWP. The mediating effect of PersA (.142) is not significant since BootCI [-.112; .412]. On the basis of this test of mediation, the null hypothesis is not rejected. Agreeableness does not mediate the relationship between technological propensity and CWP. The results of regression testing for Hypothesis A5 are summarised in Table 56, below.

Table 56: Results of Regressions for Hypothesis A5: Personality mediates the relationship between technological propensity and CWP

Personality	Mediating effect	BootCI	Null hypothesis	Direction
Openness to Experience	.150	[-.042; .363]	Not rejected	-
Extraversion	-.207	[-.464; .016]	Not rejected	-
Conscientiousness	.084	[.001; .230]	Rejected	
Neuroticism	.147	[-.017; .363]	Not rejected	-
Agreeableness	.142	[-.112; .412]	Not rejected	-

5.3.4.5 Hypothesis A6: Motivational Values mediate the relationship between technological propensity and CWP

The results of mediation testing for Hypothesis A6 are reported, as follows.

5.3.4.5.1 Hypothesis A6.1: Self-Transcendence significantly mediates the relationship between technological propensity and CWP

Technological propensity (.992; p<.000) predicts self-transcendence (MotST). Of the covariates, only Age (-.011; p<.033) predicts MotST. Neither MotST (.012; p<.898), nor technological propensity (.002; p<.994) predict CWP. The only significant covariate predictors of CWP are Age (.027; p<.000) and Nat3Other (-.883; p<.010). The mediating effect of MotST (.012) is not significant since BootCI [-.161; .197]. Based on this result, the null hypothesis is not rejected. Self-transcendence does not significantly mediate the relationship between technological propensity and CWP.

5.3.4.5.2 Hypothesis 6A.2: Openness to Change significantly mediates the relationship between technological propensity and CWP

Technological propensity (.883; p<.000) predicts openness to change (MotOC); there were no significant covariate predictors of MotOC. MotOC (-.029; p<.808) does not predict CWP, nor does technological propensity (.039; p<.885). The only significant covariate predictors of CWP are Age (.027; p<.000) and Nat3Other (-.874; p<.011). The mediating effect of MotOC (-.026) is not significant since BootCI [-.242; .176]. Therefore, the null hypothesis is rejected. Openness to change does significantly mediate the relationship between technological propensity and CWP.

5.3.4.5.3 Hypothesis A6.3: Conservation mediates the relationship between technological propensity and CWP

Technological propensity (.556; p<.000) predicts conservation (MotC), as does Age (.011; p<.016). Neither MotC (.016; p<.874), nor technological propensity (.004; p<.986) predicts CWP. Significant covariate predictors of CWP included Age (.027; p<.000) and Nat3Other (-.879; p<.010). The mediating effect of MotC (.009) is not significant since BootCI [-.107;

.124]. Therefore, the null hypothesis is not rejected. Conservation does not significantly mediate the relationship between technological propensity and CWP.

5.3.4.5.4 Hypothesis A6.4: Self-Enhancement significantly mediates the relationship between technological propensity and CWP

Technological propensity (1.000; p<.000) does predict self-enhancement (MotSE), as does Age (-.010; p<.029). Neither MotSE (-.010; p<.914) nor technological propensity (.024; p<.927) predict CWP. Covariates Age (.027; p<.001) and Nat3Other (-.877; p<.011) do predict CWP. The mediation effect of MotSE (-.010) is not significant since BootCI [-.195; .196]. On the basis of this analysis, the null hypothesis is not rejected. Self-enhancement does not significantly mediate the relationship between technological propensity and CWP. The results of regression testing for Hypothesis A6 are summarised in Table 57, as follows.

Table 57: Results of Regressions for Hypothesis A6: Motivational values mediate the relationship between technological propensity and CWP

Motivational Values	Mediating effect	BootCI	Null hypothesis	Direction
Self-Transcendence	.012	[-.161; .197]	Not rejected	-
Openness to Change	-.026	[-.246; .176]	Rejected	(-.026; p<.000)
Conservation	.009	[-.107; .124]	Not rejected	-
Self-Enhancement	-.010	[-.195; .196]	Not rejected	-

5.3.4.6 Hypothesis A8: Human Capital Investments (HCI) mediate the relationship between technological propensity and CWP.

Technological propensity (.193; p<.054) does not predict HCI. Significant covariate predictors of HCI included Nat1USA (-.413; p<.000) and Lan1Eng (.222; p<.012) HCI (.109; p<.412) and technological propensity (.013; p<.957) do not predict CWP. Significant covariate predictors of CWP include Age (.027; p<.000) and Nat3Other (-.880; p<.010). The mediating effect of HCI (.021) is not significant since BootCI [-.021; .111]. The null hypothesis is not rejected. HCI do not significantly mediate the relationship between technological propensity and CWP.

5.3.4.7 Hypothesis B1: Human Capital Investments (HCI) are significantly associated with CWP

In Model 1, covariates (R^2 =.043, p<.003) account for a total of 4.3% of significant variance in the regression model. In Model 2, the inclusion of the independent variable HCI (R^2 = .044; p<.415) accounts for a further .1% of total variance, but this was not significant. The specification is represented as follows:

> Y(CWP) = 6.466 +.027(Age) -.089(Gender) -.092(Nat1USA) -.881(Nat3Other) -.246(Lan1Eng) -.132 (Children) -.305(Profession) + .110(HCI).

Significant standardised covariates include Age (.147; p<.002) and Nat3Other (-.118; p<.014). The independent variable, HCI (.037; p<.415) is not significant. The null hypothesis is not rejected. HCI are not significantly associated with CWP.

5.3.4.8 Hypothesis B2: Personality mediates the relationship between Human Capital Investments (HCI) and CWP

The results of mediation testing for Hypothesis B2 are now reported. Each of the Big Five constructs of personality are tested for their mediating effect on the relationship between HCI and CWP, as follows.

5.3.4.8.1 Hypothesis B2.1: Openness to Experience mediates the relationship between HCI and CWP

HCI (.145; p<.035) does predict openness to experience (PersO). Significant covariate predictors of PersO includes Children (-.096; p<.041) only. Neither PersO (.121; p<.152), nor HCI (.092; p<.489) significantly predict CWP. Significant covariates of CWP include Age (.027; p<.000) and Nat3Other (-.872; p<.010). The mediating effect of PersO (.018) is not significant since BootCI [-.002;.066]. On the basis of this analysis, the null hypothesis is not rejected. Openness to experience does not mediate the relationship between HCI and CWP.

5.3.4.8.2 Hypothesis B2.2: Extraversion significantly mediates the relationship between HCI and CWP

HCI (.107; p<.225) does not predict extraversion (PersE). Significant covariate predictors of PersE include Nat1USA (-.808; p<.000), Nat3Other (-.548; p<.009) and Lang1Eng (.312; p<.046) Neither PersE (-.106; p<.122) nor HCI (.121; p<.358) significantly predict CWP. Significant covariate predictors of CWP include Age (.027; p<.000) and Nat3Other (-.939; p<.006). The mediating effect of PersE (-.011) is not significant since BootCI [-.054; .004]. Therefore, the null hypothesis is not rejected. Extraversion does not mediate the relationship between HCI and CWP

5.3.4.8.3 Hypothesis B2.3: Conscientiousness significantly mediates the relationship between HCI and CWP

HCI (-.028; p<.651) does not predict conscientiousness (PersC). The only significant covariate predictor of PersC is Age (.022; p<.000). Neither PersC (.175; p<.086), nor HCI (.115; p<.382) significantly predict CWP. Covariates Age (.023; p<.002) and Nat3Other (-.889; p<.009) do significantly predict CWP. The mediating effect of PersC (-.005) is not significant since BootCI [-.041; .013]. Based on this result, the null hypothesis is not rejected. Conscientiousness does not mediate the relationship between HCI and CWP.

5.3.4.8.4 Hypothesis B2.4: Neuroticism significantly mediates the relationship between HCI and CWP

HCI (-.001; p<.992) does not predict neuroticism (PersN). Age (-.023; p<.000), Gender (-.425; p<.000) and Nat3Other (.431; p<.016) are all significant covariate predictors of PersN. Neither PersN (-.133; p<.118) nor HCI (.110; p<.406) significantly predict CWP. Covariates Age (.024; p<.002) and Nat3Other (-.824; p<.016) are significant predictors of CWP. The mediating effect of PersN (.000) is not significant since BootCI [-.027; .025]. The null hypothesis is therefore not rejected. Neuroticiscm does not mediate the relationship between HCI and CWP.

5.3.4.8.5 Hypothesis B2.5: Agreeableness significantly mediates the relationship between HCI and CWP

HCI (-.019; p<.771) does not predict agreeableness (PersA). Significant covariate predictors of PerA include Age (.022; p<.000), Nat1USA (-.531; p<.000) and Nat3Other (-.470; p<.003). Neither PersA (.092; p<.318) nor HCI (.112; p<.400) significantly predict CWP. Significant covariate predictors of CWP include Age (.025; p<.001) and Nat3Other (-.838; p<.016). The mediating effect of PerA (-.002) is not significant since BootCI [-.031; .009]. Based on this analysis, the null hypothesis is not rejected. Agreeableness does not mediate the relationship between HCI and CWP.

Table 58: Results of Regressions for Hypothesis B2: Personality mediates the relationship between HCI and CWP

Personality	Mediating effect	BootCI	Null hypothesis	Direction
Openness to Experience	.018	[-.002;.066]	Not rejected	-
Extraversion	-.011	[-.054; .004]	Not rejected	-
Conscientiousness	-.005	[-.041; .013]	Not rejected	-
Neuroticism	.005	[-.018; .041]	Not rejected	-
Agreeableness	-.002	[-.031; .009]	Not rejected	-

5.3.4.9 Hypothesis B3: Motivational Values mediate the relationship between Human Capital Investments (HCI) and CWP

The results of mediation testing for Hypothesis B3 are now reported. Each of Schwartz' (1992) higher-order motivational values are tested for their mediating effect on the relationship between HCI and CWP.

5.3.4.9.1 Hypothesis B3.1: Self-Transcendence significantly mediates the relationship between HCI and CWP

HCI (.046; p<.534) does not predict self-transcendence (MotST), nor do any of the predictor covariates in the mediation model. Neither MotST (.012; p<.891), nor HCI (.109; p<.412)

predict CWP. Only Age (.027; p<.000) and Nat3Other (-.883; p<.009) as covariate predictors of CWP are significant. The mediating effect of MotST (.001) is not significant, since BootCI [-.011; .025]. Based on this result, the null hypothesis is not rejected. Self-transcendence does not mediate the relationship between HCI and CWP.

5.3.4.9.2 Hypothesis B3.2: Openness to Change significantly mediates the relationship between HCI and CWP

Neither HCI (.108; p<.088), nor any of the covariate predictors in the mediation model significantly predict CWP. Both openness to change (MotOC) (-.025; p<.823) and HCI (.113; p<.403) do not significantly predict CWP. The only covariate predictors that significantly predicts CWP are Age (.027; p<.000) and Nat3Other (-.879; p<.009). The mediating effect of MotOC (-.003) is not significant since BootCI [-.038; .021]. The null hypothesis is therefore not rejected. Openness to change does not mediate the relationship between HCI and CWP.

5.3.4.9.3 Hypothesis B3.3: Conservation significantly mediates the relationship between HCI and CWP

HCI (.046; p<.526) does not predict conservation (MotC), nor do any covariates. Neither MotC (.017; p<.870) nor HCI (.109; p<.413) significantly predict MotC. Covariates predictors Age (.027; p<.000) and Nat3Other (-.880; p<.009) do significantly predict MotC. The mediation effect of MotC (.001) is not significant since BootCI [-.012; .024]. On the basis of the analysis, the null hypothesis is therefore not rejected. Conservation does not mediate the relationship between HCI and CWP

5.3.4.9.4 Hypothesis B3.4: Self-Enhancement significantly mediates the relationship between HCI and CWP

HCI (.148; p<.040) does predict self-enhancement (MotSE), as does Age (-.015; p<.002). Neither MotSE (-.009; p<.927), nor HCI (.111; p<.408) significantly predict CWP. Covariate predictors Age (.027; p<.001) and Nat3Other (-.880; p<.009) do significantly predict CWP. The mediation effect of MotSE (-.001) is not significant, since BootCI [-.035; .029]. The null hypothesis is therefore not rejected. Self-enhancement does not mediate the relationship

between HCI and CWP. The results of regression testing for Hypothesis B3 are summarised in Table 59, as follows.

Table 59: Results of Regressions for Hypothesis B3: Motivational values mediate the relationship between HCI and CWP

Motivational Values	Mediating effect	BootCI	Null hypothesis	Direction
Self-Transcendence	.001	[-.011; .025]	Not rejected	-
Openness to Change	-.003	[-.038; .021]	Not rejected	-
Conservation	.001	[-.012; .024]	Not rejected	-
Self-Enhancement	-.001	[-.035; .029]	Not rejected	-

5.3.4.10 Hypothesis C1: Gender significantly moderates the relationship between technological propensity and CWP

Tests of moderation were conducted following the same procedure as for the academic researcher sample, using Hayes' (2013) PROCESS for moderation. All tests of moderation were conducted with 5000 bootstrap iterations. In each test of moderation that follows, the independent variable is mean split into 'high' and 'low'.

The results of the moderation analysis show that the interaction term (technological propensity x Gender) is not a significant predictor of the outcome, CWP (3989.025; p<.298). Thus, gender does not significantly moderate the relationship between technological propensity and CWP. Based on this result, the null hypothesis is not rejected. The moderation plot for Hypothesis C1 is depicted in Figure 30, below.

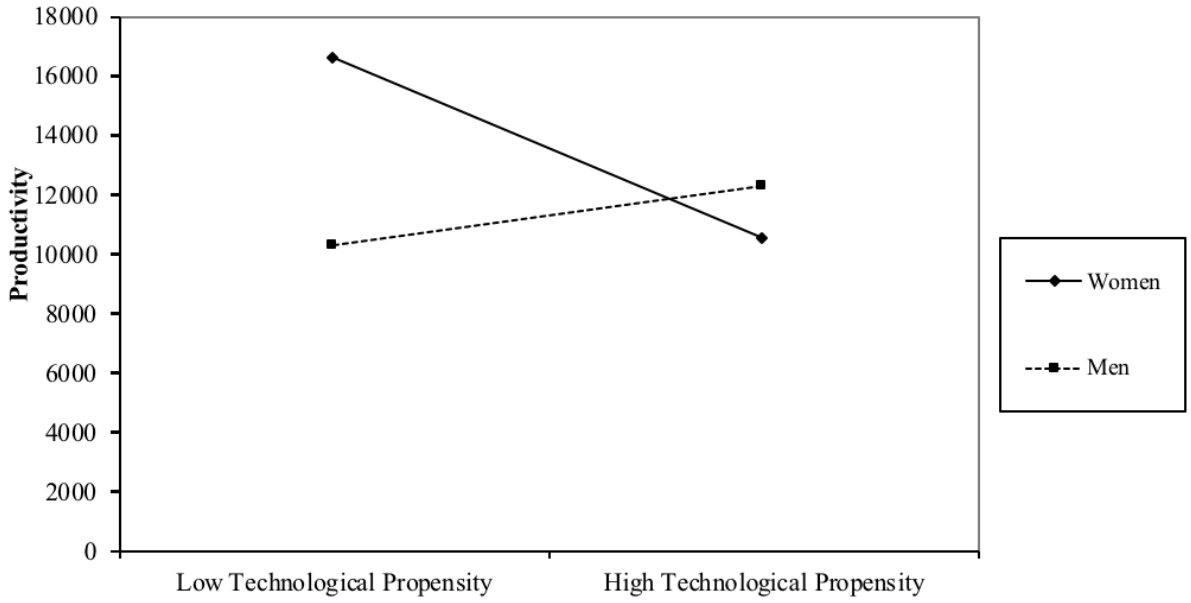


Figure 30: Hypothesis C1 (crowd-worker sample) moderation plot

Examination of the interaction plot shows that men respondents seem to have lower rates of productivity at low levels of technological propensity but higher rates of productivity at high levels of technological propensity. Women respondents seem to have higher rates of productivity at low levels of technological propensity but lower rates of productivity at high levels of productivity. According to the results of the analysis however, the difference in slopes is not significant.

5.3.4.11 Hypothesis C2: Profession significantly moderates the relationship between technological propensity and CWP

For the crowd-worker sample, profession was converted into a binary measure. Respondents in STEM professions (and, who are expected to be associated with higher levels of technological propensity) are represented by a 1. Respondents in other, non-STEM professions, are represented by a 0. The interaction between technological propensity and profession (765.609; $p<.909$) is not a significant predictor of CWP. Based on this analysis, the null hypothesis is not rejected. Profession does not significantly moderate the relationship between technological propensity and CWP. The moderation plot for Hypothesis C2 is depicted in Figure 31, below.

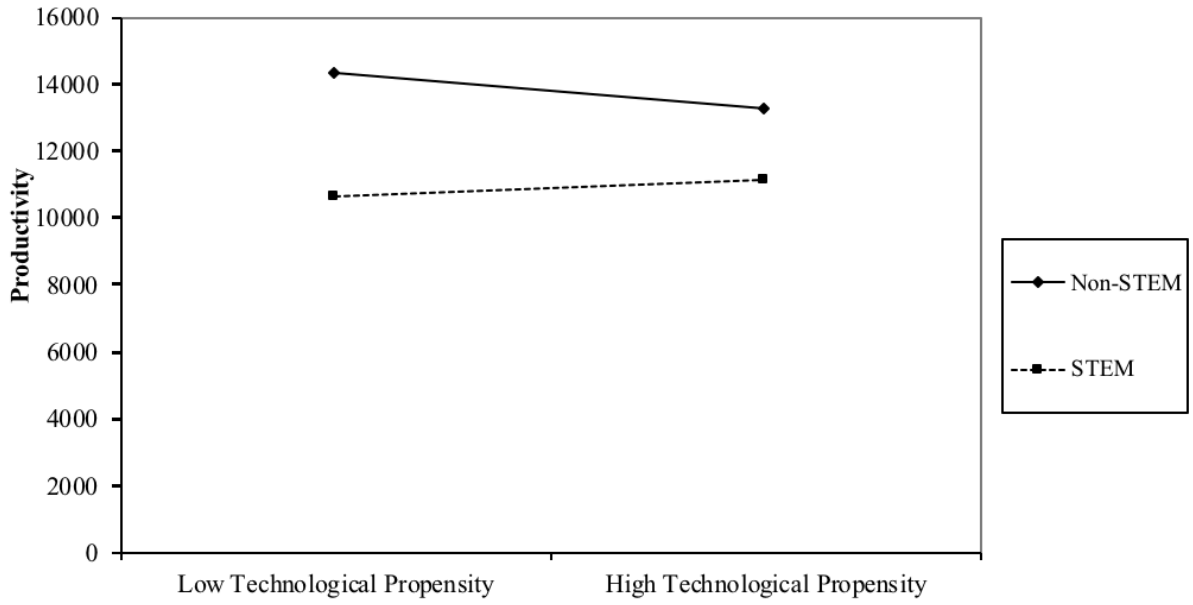


Figure 31: Hypothesis C2 (crowd-worker sample) moderation plot

Examination of the interaction plot shows that respondents in STEM professions seem to have lower rates of productivity at both low land high levels of technological propensity. The same applies to respondents in non-STEM professions, but at higher rates of productivity. According to the results of the analysis however, the difference in slopes is not significant.

5.3.4.12 Hypothesis C3: Gender significantly moderates the relationship between Human Capital Investments (HCI) and CWP

The interaction between HCI and gender is not a significant predictor of CWP (-1762.325; p<.478). Based on this result, the null hypothesis is not rejected. Gender does not moderate the relationship between HCI and CWP. The moderation plot for Hypothesis C3 is depicted in Figure 32, below.

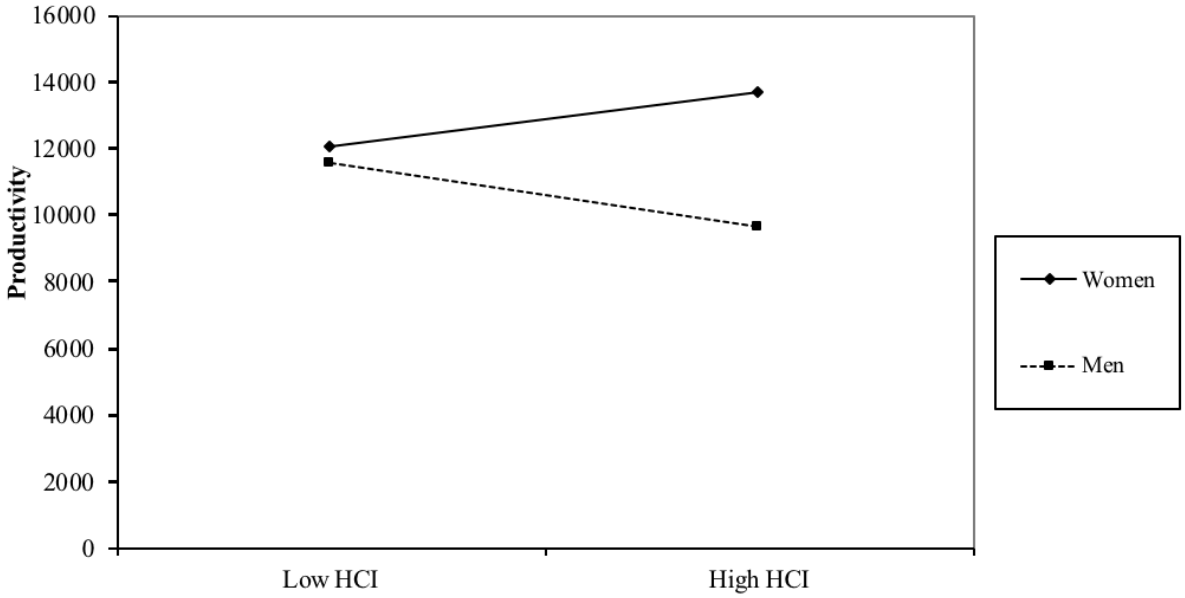


Figure 32: Hypothesis C3 (crowd-worker sample) moderation plot

Examination of the interaction plot shows that men respondents seem to have lower rates of productivity at both low land high levels of HCI. The same applies to women respondents, but at higher rates of productivity. According to the results of the analysis however, the difference in slopes is not significant.

5.3.4.13 Hypothesis C4: Profession significantly moderates the relationship between Human Capital Investments (HCI) and CWP

The interaction between HCI and profession is not a significant predictor of CWP (-105.186; p<.949). Based on this analysis, the null hypothesis is not rejected. Profession does not moderate the relationship between HCI and CWP. The moderation plot for Hypothesis C4 is depicted in Figure 33, below.

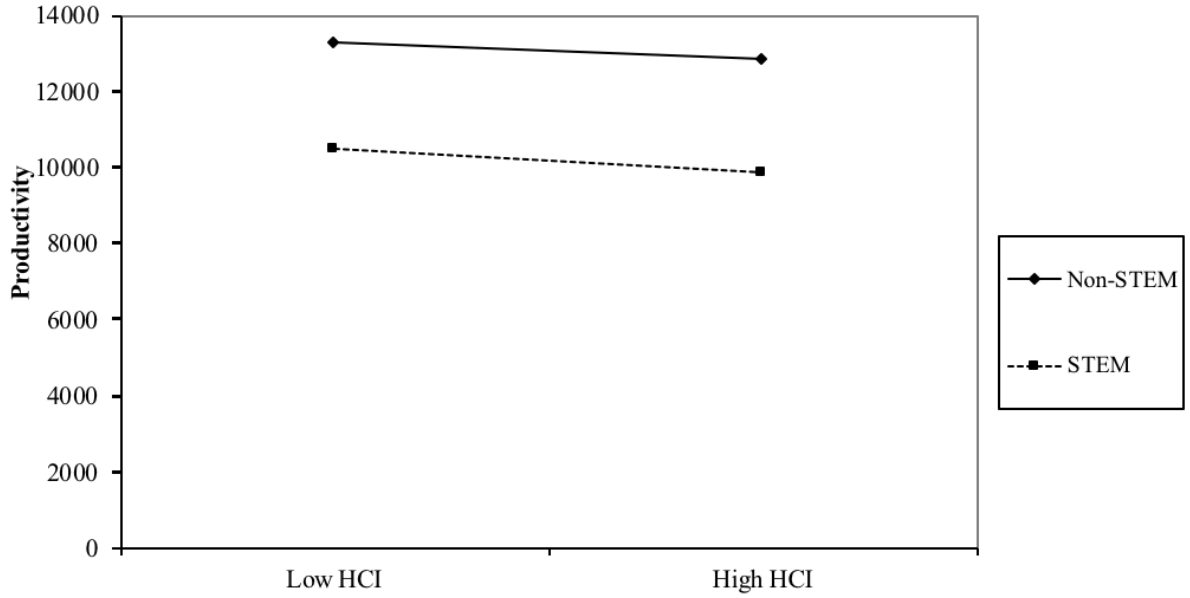


Figure 33: Hypothesis C4 (crowd-worker sample) moderation plot

Examination of the interaction plot shows that respondents in STEM professions seem to have lower rates of productivity at both low land high levels of HCI. The same applies to respondents in non-STEM professions, but at higher rates of productivity. According to the results of the analysis however, the difference in slopes is not significant. The results of the tests of moderation for Hypothesis C are summarised in Table 78, below.

Table 60: Results of Tests of Moderation

Hypothesis	Test of Moderation	Null Hypothesis	Direction
C1	Gender moderates technological propensity-CWP	Not rejected	-
C2	Field moderates technological propensity-CWP	Not rejected	-
C3	Gender moderates HCI-CWP	Not rejected	-
C4	Field moderates HCI-CWP	Not rejected	-

Examination of the interaction plots above, shows that although there may be differences in the relationship between HCI and productivity by field of study, none of these differences are significant. Since field of study does not significantly moderate the relationship between HCI and productivity, the null hypothesis is not rejected. This concludes the result of the crowd-worker analysis. The results of all crowd-worker multivariate tests are summarised in Table 79, below. Thereafter, this chapter is concluded.

Table 61: Results of Multivariate Analyses (Crowd-Worker Sample)

Research Question A	What is the relationship between technological propensity and productivity?	Null Hypothesis
Hypothesis A1	Technological propensity is significantly associated with Productivity.	Not rejected
Hypothesis A2	Personality is significantly associated with technological propensity.	
Hypothesis A2.1	Openness to experience is significantly associated with technological propensity	Rejected
Hypothesis A2.2	Extraversion is significantly associated with technological propensity	Rejected
Hypothesis A2.3	Conscientiousness is significantly associated with technological propensity	Rejected
Hypothesis A2.4	Agreeableness is significantly associated with technological propensity	Rejected
Hypothesis A2.5	Neuroticism is significantly associated with technological propensity	Rejected
Hypothesis A3	Motivational Values are significantly associated with technological propensity	
Hypothesis A3.1	Self-transcendence is significantly associated with technological propensity	Rejected
Hypothesis A3.2	Openness to change is significantly associated with technological propensity	Rejected
Hypothesis A3.3	Conservation is significantly associated with technological propensity	Rejected
Hypothesis A3.4	Self-enhancement is significantly associated with technological propensity	Rejected
Hypothesis A6	Personality mediates the relationship between technological propensity and productivity.	
Hypothesis A6.1	Openness to experience significantly mediates the relationship between technological propensity and productivity	Not rejected
Hypothesis A6.2	Extraversion significantly mediates the relationship between technological propensity and productivity	Not rejected
Hypothesis A6.3	Conscientiousness significantly mediates the relationship between technological propensity and productivity	Not rejected
Hypothesis A6.4	Agreeableness significantly mediates the relationship between technological propensity and productivity	Not rejected
Hypothesis A6.5	Neuroticism significantly mediates the relationship between technological propensity and productivity	Not rejected
Hypothesis A7	Motivational Values mediate the relationship between technological propensity and productivity.	
Hypothesis A7.1	Self-Transcendence significantly mediates the relationship between technological propensity and productivity.	Not rejected
Hypothesis A7.2	Openness to change significantly mediates the relationship between technological propensity and productivity.	Not rejected

Hypothesis A7.3	Conservation significantly mediates the relationship between technological propensity and productivity.	Not rejected
Hypothesis A7.4	Self-Enhancement significantly mediates the relationship between technological propensity and productivity.	Not rejected
Hypothesis A9	Human Capital Investments (HCI) mediate the relationship between technological propensity and productivity.	Not rejected
Research Question B	What is the relationship between Human Capital Investments (HCI) and productivity?	
Hypothesis B1	Human Capital Investments (HCI) are significantly associated with productivity.	Not rejected
Hypothesis B2	Personality mediates the relationship between Human Capital Investments (HCI) and productivity.	
Hypothesis B2.1	Openness to Experience significantly mediates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis B2.2	Extraversion significantly mediates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis B2.3	Conscientiousness significantly mediates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis B2.4	Agreeableness significantly mediates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis B2.5	Neuroticism significantly mediates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis B3	Motivational Values mediate the relationship between Human Capital Investments (HCI) and productivity.	
Hypothesis B3.1	Self-transcendence mediates the relationship between Human Capital Investments (HCI) and productivity.	Not rejected
Hypothesis B3.2	Openness to change mediate the relationship between Human Capital Investments (HCI) and productivity.	Not rejected
Hypothesis B3.3	Conservation mediate the relationship between Human Capital Investments (HCI) and productivity.	Not rejected
Hypothesis B3.4	Self-Enhancement mediate the relationship between Human Capital Investments (HCI) and productivity.	Not rejected
Research Question C	What are the interactive effects of gender and field of study on the relationships between technological propensity, Human Capital Investments (HCI) and productivity?	
Hypothesis C1	Gender significantly moderates the relationship between technological propensity and productivity	Not rejected
Hypothesis C2	Profession significantly moderates the relationship between technological propensity and productivity	Not rejected
Hypothesis C3	Gender significantly moderates the relationship between Human Capital Investments (HCI) and productivity	Not rejected
Hypothesis C4	Profession significantly moderates the relationship between Human Capital Investments (HCI) and productivity.	Not rejected

5.4 CHAPTER CONCLUSION

In this chapter, the results of the quantitative research were reported. This chapter was split into two sections. In the first section (Section A), the results of analysis of data from the South African academic researcher sample were reported. In the second section (Section B), the results of analysis of data from the crowd-worker sample were reported. For both samples, univariate, bivariate and multivariate statistical analyses were conducted. The results of these analyses were reported in this chapter. Firstly, for each sample, univariate analyses were conducted. This included a report on biographical details and general trends. Measures, location, central tendency and statistical dispersion of the major variables under study were reported. The means, medians, mode values, standard deviations and variances were derived, and these were then reported in the following sections. The univariate analysis measures of normality were also reported. Measures of skewness and kurtosis statistics were provided. Tests of bivariate correlation were also conducted for each sample. Bivariate characteristics of the data that have implications for the interpretation of results, were reported. These tests were not used to test hypotheses but were reported under the headings of the hypotheses for ease of reporting and are used in the proceeding chapter to support the results of the multivariate analyses. Finally, for each sample, multivariate analyses were conducted. These included tests of hierarchical multiple regression, mediation and moderation. Tests of moderation produced moderation plots, which were reported. These analyses were used to test the hypotheses. The results of the tests of each hypothesis were reported in tables, for the academic researcher and crowd-worker sample, respectively. Reporting of qualitative results (Chapter) and quantitative results (Chapter 5) is now concluded. Chapter 6, which contains a discussion of both qualitative and quantitative results, in relation to the literature, now follows.

CHAPTER 6
DISCUSSION OF THE FINDINGS

6.1 INTRODUCTION

In this chapter, the results of the qualitative and quantitative analyses are discussed. This chapter extends the investigation from a reporting of the results to a discussion of the results. In Chapter 3, the methodology and statistical tests applied to the data were outlined and explained. The qualitative analysis was discussed in Chapter 4. In Chapter 5, the results of the statistical testing were reported. In this chapter, the results of Studies 1 (the qualitative study), 2 (the academic researcher analysis) and 3 (the crowd-worker sample) are examined and discussed in relation to literature. The structure of this chapter follows the derivation of propositions from the qualitative study and the tested hypotheses from the quantitative studies. This chapter is split into three sections. In the first section, qualitative findings are discussed in relation to derived propositions. In the second section, quantitative findings are discussed in relation to hypotheses derived from theory in the form of the theoretical model. In the third section, a synthesis of qualitative and quantitative findings and literature is provided. The chapter concludes with a summary. A discussion of the qualitative findings now follows.

6.2. DISCUSSION OF QUALITATIVE FINDINGS

The findings of the qualitative analysis are now discussed in relation to the literature. First, the biographical details of the qualitative sample are reported. Next, the propositions that were derived from qualitative data are discussed, in relation to literature. Two overarching propositions were derived. These include Proposition A: internal drivers are related to BRP and Proposition B: External drivers are related to BRP. The biographical details and general trends of the qualitative sample are now discussed, as follows.

6.2.1 Biographical details

The qualitative sample comprised of 30 individuals with an average age of 73.5 years. This relatively advanced age may be attributed to the fact that notable prizes (such as the Nobel Prize, the Wolf Prize, and the Lasker Award) are generally awarded to well-established and highly experienced individuals, who tend to be older than their peers (Jones, 2010). The sample consisted of 26 male respondents (86.7%) and 4 female respondents (13.3%). This contrast reflects the unfortunate gender gap in major scientific and academic prizes, although it is purported that this gap is gradually decreasing (Wagner, 2016). In terms of nationality, the

sample mostly comprised of Americans (63.3%). Most of the remainder of the sample were from Europe and the UK. A smaller percentage came from other countries, including two South Africans. However, the sample was skewed heavily in favour of respondents from Western and developed countries, reflecting the disproportionate nature of major scientific awards (Williams, 1990; Mazloumian, Eom, Helbing, Lozano & Fortunato, 2011).

6.2.2 Discussion of Propositions

Two overarching propositions were derived from qualitative analyses. These include i) Proposition A: internal drivers are related to BRP and ii) Proposition B: external drivers are related to BRP. Proposition A is discussed first, as follows.

6.2.2.1 Proposition A: Internal Drivers are related to BRP (Internal drivers such as personalities, motivations, innate abilities and technological Propensity aligned to breakthrough research behaviours are positively related to BRP)

Internal drivers refer to intangible characteristics that cannot be separated from the individual. The matter of whether inherent, individual-level characteristics impact on productivity as a product of 'nature or nurture' has been widely debated (Behrman & Taubman, 1989; Blazer & Hernandez, 2006; Bartelt & Dennis, 2014). Nevertheless, to assess the determinants of BRP, respondents were asked what they thought were important characteristics of individuals that would enable the production of breakthrough research. Responses generally fell into four broad categories. These include i) personality, ii) motivation, iii) innate ability and iv) technological propensity. Each of these is now discussed in relation to BRP, as follows.

6.2.2.1.1 Personality is related to BRP (Humble, enthusiastic, open, conscientious and extraverted personalities are positive drivers of BRP)

According to Larson and Buss (2010, p. 4), personality is "the set of psychological traits and mechanisms within the individual that are organised and relatively enduring and that influence his or her interactions with, and adaptations to, the intra-psychic, physical and social environments." Although there are several models of personality, empirical research has shown that the "trans-theoretical nature" (Costa & McCrae, 1990, p. 1) of the 'Big Five' model of personality is able to account for different personality traits, without overlapping (Boyle,

2008). The Big Five model of personality is perhaps the most widely used model of personality in social science research (Saucier & Srivastava, 2015). Following Costa and McCrae (1995), the Big Five model of personality comprises of five broad personality dimensions. These include i) neuroticism, ii) agreeableness, iii) continuousness, iv) openness to experience and v) extraversion. To investigate the drivers of BRP, respondents were asked the question:

> *"In your experience, which personality factors do you think contribute to attaining a research breakthrough?"*

The findings of the analysis suggest that conducive personality traits are imperative in the production of breakthrough research. The findings seem to indicate a broad adherence to the Big Five model of personality, albeit with some differences. Five sub-themes related to personality emerged from qualitative data. These included the following: i) openness, ii) conscientiousness, iii) enthusiasm, iv) extraversion and v) humility. Since respondents were unlikely to advocate neuroticism or agreeableness as catalysts for breakthrough research, it follows that these may be substituted by personality traits that are more in line with 'breakthrough' personalities. In this case, neuroticism and agreeableness were replaced with humility and enthusiasm. Each of these broad personality characteristics, derived from qualitative analysis, are now discussed.

Openness

Following the Big Five model of personality, openness to experience is defined as a combination of curiosity, creativity, independence, imaginativeness and a preference of variety and novelty (Atkinson, et al., 2014). Others have defined openness to experience as "an appreciation for experience…. intellectually curious, open to emotion and sensitive to beauty and the pursuit of self-actualisation" (Costa & MCrae, 1990, p. 366). According to McCrae and John (1992), openness to experience is a personality characteristic attributed to individuals who are artistic, curious, imaginative, insightful, original and who have wide interests.

In describing personalities conducive to attaining research breakthroughs, respondents often referred to curiosity, creativity, imagination and inventiveness. Curiosity was the most frequently cited of these. This was commonly manifested in the "ability to ask questions" (R11) and challenge established schools of thought. Creativity, also referred to as 'inventiveness' was

also associated with independent thought. However, creativity was differentiated from curiosity, as an ability to draw conclusions that are outside the norm.

Previous studies have investigated the association between age and personality. Specht, Egloff and Schmukle (2011, p. 6) find that "the development of openness has shown a curvilinear pattern, increasing in early adulthood and decreasing in old age." Costa and McCrae (1990) note that individuals with lower levels of openness to experience tend to follow conventional ways of thinking and in some cases, may also be more risk averse than others (Barrick et al., 1998). Given that the qualitative sample comprised primarily of respondents older than 60 (with a mean age of 73.5 years), a general decrease in openness to experience may be expected. In some cases, respondents were critical of open thinking, citing a preference for conventional, tried and tested methods of scientific research. This finding may be attributable to age. Many also described openness as a luxury only affordable to those have understood "*what's going on in the box, before [one] goes outside the box*" (R10). In other words, that the pursuit of radical innovations is only possible following extensive education and experience. Respondents that were female, or from developing countries, generally tended to have differing views on the relationship between openness to experience and BRP. These respondents also tended to have more *diverse* HCI. HCI diversity refers to a varied accumulation of education, training and experience. Conversely, as a general trend, male respondents and respondents from developed countries tended more towards traditional methods of scientific research. These respondents also tended to have more conventional and linear progressions of HCI.

Bourdieu (1992) uses the term habitus to describe a set of acquired schemes of dispositions, perceptions and appreciations, which orient practices and give them meaning, as a result of actions and interactions with others. According to Thorpe (2009, p. 499), habitus is "both the embodiment of our social location (i.e. class, ethnicity, race, sexuality, gender, generation and nationality) … and the structure of social relations that generate and give significance to likes and dislikes with regard to practice and action." Following both Bourdieu (1992) and Thorpe (2009), gender and nationality may therefore represent the embodiment of experiences and socialisations that individuals are exposed to. This finding therefore may suggest that gender and nationality may moderate the relationship between personality and BRP. HCI and HCI diversity is discussed further in section 6.2.2.2.1. As previously mentioned, some respondents rejected the notion of openness, in favour of conventional or traditional approaches to scientific research. Such respondents often referred to the importance of conscientiousness.

Conscientiousness

For Costa and McCrae (1992), conscientiousness is associated with the manner in which people control, regulate and direct their impulses. Following McCrae and John (1992), conscientious individuals are efficient, organised, reliable, responsible and thorough. Several studies have discovered strong associations between conscientiousness and work performance (or, productivity) (Barrick & Mount, 1991; Hurtz & Donavan, 2000; Judge & Zapata, 2015). Conscientious individuals tend to pursue achievement, are dutiful and inclined to prefer planned, rather than spontaneous behaviour (McCrae & Costa, 1989; Gebauer, Bleidom, Gosling, Rentfrow, Lamb, & Potter, 2016). However, conscientious individuals may be viewed in a negative light, as stubborn or obsessive. Conversely, individuals who are not conscientious tend to be more flexible and spontaneous, which may be perceived as unreliability (Costa & McCrae, 1992).

In terms of the qualitative analysis, conscientiousness was most commonly associated with perseverance and persistence. There was however, divided opinion as to what these terms mean. For some, being conscientious entails a consistent critical approach applied to the scientific research process. For these respondents, independent thought lies at the heart of attaining breakthroughs. Independent thought is also associated with openness. This suggests a link between openness and conscientiousness, in this context. Other respondents remarked that conscientiousness is more closely related to traditional ideals such as “hard work” (R11) and “focus” (R30). In this sense, conscientiousness refers to an aggressive pursuit of standards and norms, rather than an aggressive pursuit of independence. In both cases however, most respondents agreed that strongly persistent and perseverant attitudes will help to attain breakthrough objectives.

While these findings may differ somewhat from established definitions of conscientiousness (Costa & McCrae, 1990; McCrae & John, 1992; Gebauer, et al., 2016), they do support the definition of conscientiousness that includes ‘control’ and ‘responsibility. As per the findings of this analysis, such individuals eschew risky or spontaneous behaviours in favour of those that are planned and organised, whether those behaviours are geared toward independent thought and creativity, or toward hard work and focus. In both cases, many respondents associated conscientiousness with enthusiasm.

Enthusiasm

According to the typology put forth by McCrae and John (1992), enthusiasm is a form of extraversion. Following the results of the qualitative analysis however, enthusiasm was differentiated from extraversion. This is because extraversion was found to relate more closely to social interactions, while enthusiasm relates to passion for scientific research. This category of personality emerged strongly from qualitative analysis. Many respondents referred to enthusiasm as a crucial prerequisite to attaining BRP. Enthusiasm was also referred to as a 'thirst' or 'hunger' for knowledge and a desire to find solutions to problems. Terms such as 'energy', 'excitement' and 'passion' were used to describe personality types that pursue breakthrough objectives as a means to quell intrinsic desire for knowledge. This was frequently cited as one of the strongest drivers of breakthrough performance.

This sub-theme linked closely to that of openness. In particular, enthusiasm may be closely associated with curiosity. This sub-theme may also be associated with the greater theme of motivational values. This is because enthusiasm is seen as a powerful motivational force, owing to its' intrinsic nature. Further analysis revealed that intrinsic motivators are often more powerful than extrinsic motivators. This differentiation is also strongly supported by literature (Deci & Ryan, 2000; Tremblay, et al., 2009). Enthusiasm also linked closely to the sub-theme of extraversion. As previously mentioned, typologies of Big Five personality traits often list enthusiasm as a sub-component of extraversion.

Extraversion

Extraverted individuals are those who are outgoing, energetic, sociable and assertive (Atkinson, et al., 2014). Extraverted individuals tend to seek stimulation in the company of others and are generally talkative and action-oriented. However, high extraversion can also equate to attention-seeking and domineering individuals (Costa & McCrae, 1990).

Qualitative analysis revealed "*interactive skills*" (R25) and the "*ability to collaborate with others*" (R23) as important contributors to attaining breakthrough productivity. Collaboration emerged as the strongest key concept related to extraversion. This was particularly true of respondents in fields such as experimental physics, which often involve significantly large-

scale projects that entail the collaborations of hundreds, sometimes thousands of scientists (for example, experiments conducted at the Large Hadron Collider at CERN). However, the analysis also revealed a high degree of introversion amongst the sample. Some respondents reported their dislike for collaboration, others mentioned that they strive to avoid collaborating with other scientists. These respondents generally tended to come from fields such as mathematics and statistics (or, STEM fields). This finding suggests that field of study may moderate the relationship between personality and BRP.

As a general trend however, most respondents agreed that extraversion, and by extension, collaboration, is an important contributor to breakthrough performance. This notion was linked to that of knowledge dissemination; that cross-disciplinary collaboration produces a high probability of breakthrough output, owing to interaction of diverse knowledge and diverse perspectives. This finding is strongly supported by innovation and knowledge management theory (Drucker, 1990; Nonaka, 1994; Smith, 2010). Moreover, this finding is supportive of 6G theory, which purports that exponentially increasing interaction of diverse knowledge inputs will increase the probability of producing radical innovations or breakthroughs (Callaghan, 2014a).

Communication was another key concept that was found to relate to extraversion. Some respondents associated communication with an altruistic motivation, given the importance of communicating scientific findings to society. This finding also strongly supports 6G theory; that the proprietary nature of scientific research may be a barrier to social progress. Instead, 6G theory purports that new scientific knowledge should be fed back into the system so that the probabilistic nature of knowledge can be maximised (Callaghan, 2014a; 2015a; 2015b). This finding suggests that technological propensity may mediate the relationship between personality and BRP. Individuals with extraverted personalities are more likely to produce BRP. However, the propensity to share information, knowledge and data with others, particularly those outside of the real of scientific or academic research, may strengthen this relationship. This outward-focused or, extraverted force of altruistic motivation also seems to suggest a strong degree of humility, or modesty amongst the qualitative sample. Indeed, a fifth and final sub-theme of personality, entitled ‘humility’ emerged strongly from the analysis.

Humility

Despite their status as some of the world's most successful living scientists, many respondents displayed high levels of humility, also described as humbleness. Although not considered one of the Big Five personality traits, terms such as humility and modesty have been associated with neuroticism and agreeableness, respectively (Costa, McCrae & Dye, 1991).

Neuroticism "represents… the tendency to experience distress" (McCrae, & Costa, 1989, p. 195). Neuroticism is also commonly referred to as 'emotional instability' and refers to individuals who are anxious, self-pitying, tense, unstable and worrying (McCrae & John, 1992). These characteristics however, describe the extreme end of neuroticism. Neurotic individuals may exhibit traits such as self-consciousness and vulnerability. The findings of the qualitative analysis seem to suggest that humility may be associated with these lesser forms of neuroticism. Several respondents tended to downplay their achievements, attributing their successes to chance or luck rather than ingenuity. Many others referred to the importance of humility, humbleness and "*absence of hubris*" (RR02).

Another Big Five personality trait that did not emerge from qualitative analysis is agreeableness. Digman (1990, p. 422) defines agreeableness as two opposing ends of a spectrum; "characteristics such as altruism, nurture[ing], caring and emotional support at one end … hostility, indifference to others, self-centeredness, spitefulness and jealousy at the other." Agreeable individuals tend to be appreciative, forgiving, generous, kind, sympathetic, trusting and modest (Costa & John, 1992). Amongst the qualitative sample, modesty was a key term that emerged in relation to humility. The ability to remain honest about expectations and one's own capabilities was cited as an important contributor to breakthrough productivity. The ability to set aside differences and collaborate with others was also often mentioned in conjunction with humility. Again, these findings seem to suggest that humility represents a modest form of agreeableness. Although theoretically different, the qualitative analysis unearthed many similarities between personality and motivation, in their relationship to BRP. These are discussed in the following section.

6.2.2.1.2 Motivation is related to BRP (Motivations that are intrinsic such as resilience, the pusuit of satisfaction and altruism (world view) are positive drivers of BRP)

According to Hancock (1992, p. 7) motivation is "the mainspring of behaviour; it explains why individuals choose to expend a degree of effort towards achieving particular goals." In organisational theory, one of the principal concerns is "to increase motivation in the search for greater productivity" (Thompson & McHugh, 2009, p. 307). Previous studies have investigated the relationship between motivation and productivity (Schwartz, 2006; Grant, 2008; Becker, Kernan, Clark & Klein, 2015).

There exist several different schools of thought regarding motivation and motivational values. Deci and Ryan (2000, p. 227) describe Self-Determination Theory (SDT), defined as the "nature of motivation… the why of behaviour." SDT relates to the degree to which an individual's behavior is self-motivated and self-determined, rather than extrinsically motivated. Deci and Ryan (2000) describe a self-determination continuum, which ranges from intrinsic motivation at one extreme and extrinsic motivation at the other. In contrast to personality, which offers insight into character traits, motivation may provide more comprehensive insight into intrinsic biological, social and psychological needs. Schwartz (1992) offers a formulation of motivational *values* which takes these needs into account and may help to further differentiate individuals. To assess the motivational values of individuals with high levels of BRP, qualitative respondents were asked the following question:

> *"In your experience, which motivational values do you think contribute to attaining a research breakthrough?"*

Respondents were not provided a definition of motivational values. Instead, interview questions were structured so that respondents would glean meaning from their own interpretations. Both Schwartz' (1992) model of motivational values and Deci and Ryan's (2000) self-determination continuum were reflected in the findings. The results of the analysis produced five interlinking sub-themes along the spectrum of motivation. These include i) intrinsic motivation, ii) satisfaction, iii) resilience, iv) worldview and v) extrinsic motivation. Each of these are now discussed.

Pure Intrinsic motivation

Pure intrinsic motivation emerged at the extreme end of the motivation spectrum, in a similar configuration to the self-determination continuum (Deci & Ryan, 2000). According to deCharms (1968), intrinsic motivation is a behavioural driver that comes from within an individual and that stems from will and interest. No external rewards are required to incite an intrinsically motivated person into action. Qualitative analysis revealed a powerful theme of intrinsic motivation as a key determinant of breakthrough productivity. Key terms such as 'interest', 'passion', 'desire' and 'enthusiasm' were cited frequently. Many respondents argued that intrinsic motivation is perhaps the most important motivational force to attain BRP. These findings suggest that internal motivational drivers such as curiosity, passion and a hunger for truth are far more likely to produce BRP than external motivational drivers such as financial remuneration or recognition.

Qualitative analysis also suggests that satisfaction is an important motivational driver. Unlike pure intrinsic motivation which stems from the individual, satisfaction may be considered a by-product of breakthrough success and is therefore differentiated from pure intrinsic motivation.

Satisfaction

Key phrases such as 'fun' and 'love' were used to describe satisfaction that stems from the pursuit and attainment of breakthrough productivity. This motivational force is differentiated from pure intrinsic motivation because it stems from the act of producing breakthrough research, rather than the desire to obtain breakthrough research. The key terms used to define motivational themes revealed several shared characteristics with personality. For example, 'resilience' emerged as a sub-theme of motivation. Resilience shares similarities with personality traits such as conscientiousness and enthusiasm.

Resilience

Resilience is defined as a willpower, determination and "*bloody-mindedness*" (R05), or "*stamina*" (R30) and the ability to "*take failure*" (R12). Key terms such as 'toughness', 'bravery' and 'optimism' were used to describe a motivational force akin to conscientiousness.

In other words, resilience refers to tenacity, resolve, persistence and perseverance. Qualitative analysis revealed that individuals that do not possess the fortitude to 'see things through' may experience demotivation, owing to the difficult nature of scientific research.

Given the nature of the research question which relates to *breakthrough* innovations, qualitative analysis revealed that resilience may be key in shifting from incremental to radical innovations. Several respondents referred to the difficulties in pursuing research objectives that are outside of the norm (i.e. radical). This is of particular concern in journal publication, where incremental innovations seem to be generally preferred over radical innovations. This finding suggests that the ability to persist and persevere (i.e. resilience) may help 'tip the scales' in favour of radical innovations, in some contexts.

A motivational force termed 'worldview' was also found to relate to the shift from incremental to radical innovation. Many respondents agreed that there exists a powerful altruistic motivation in the pursuit of breakthroughs. Moreover, those that experience humanistic or 'worldview' tendencies may be more strongly motivated to pursue radical innovations that lead to important social outcomes.

Worldview

The analysis revealed the importance of altruism, or the philanthropic drive to pursue research breakthroughs that will help human society. This drive is referred to as 'worldview'. Schwartz (1992) lists 'self-transcendence' as a higher-order motivational values that relates to altruistic and universal motivations. Following Schwartz' (1992) model of motivational values, self-transcendence is comprised of lower-order values such as benevolence and universalism.

Maslow (1965) defines benevolence as the preservation and enhancing of the welfare of others. Rokeach (1973) describes universalism as an understanding or appreciation for the welfare of people and nature. Both of these emerged as significant motivational forces that drive breakthrough productivity. Key terms such as 'help', 'society' and 'contributing' were used to describe the desire to apply research breakthroughs to social ends. Interestingly, this theme emerged strongly from respondents in health and medical fields. This finding suggests that field of study may moderate the relationship between motivation and BRP. This finding also

supports 6G theory, which predicts an association between radical innovation and societal externalities, such as finding cures to disease (Callaghan, 2014a).

According to SDT, extrinsic motivation exists at the polar opposite end of the SDT spectrum, in contrast to intrinsic motivation. Although not a highly significant force, analysis did reveal that some forms extrinsic motivation may contribute to breakthrough productivity.

Extrinsic Motivation

Commonly, extrinsic motivation is driven by a system of rewards and punishment (Deci, Koestner & Ryan, 1999) or by competition (Besley & Ghatak, 2003). Competition, for example, is considered an extrinsic motivational factor as the rewards (outperforming others) is independent of the intrinsic rewards (Ryan & Deci, 2000). Although not as powerful motivators as their intrinsic counterparts, extrinsic motivators were found to contribute to breakthrough productivity. Examples of extrinsic motivators include reputation, financial incentive, economic gain and 'academic glory'. These are considered extrinsic because they stem from sources external to the individual. Those respondents that did refer to extrinsic motivators also noted the superior nature of intrinsic motivation. In other words, it was revealed that intrinsic motivators are more powerful drivers of BRP. This finding is consistent with previous studies that investigated the relationship between motivation and productivity (Grant, 2008; Becker, et al., 2015).

King and Anderson (2002) provide a typology of innovative performance facilitators, at the individual level of analysis. This typology comprises of i) personality, ii) motivation, iii) job characteristics and iv) cognitive ability. As previously discussed in Chapter 2, this research is loosely based on a modified version of this typology. Cognitive ability was not directly investigated either qualitatively or quantitatively. However, qualitative analysis revealed that 'innate ability' may be an important facilitator of breakthrough productivity. The relationship between innate ability and BRP is discussed, as follows.

6.2.2.1.3 Innate ability is related to BRP (Innate abilities such as intelligence and perceptiveness are positive drivers of BRP)

Respondents were not prompted to discuss the innate skills and abilities that lead to breakthrough research productivity. However, in discussing personality and motivation, it was discovered that 'innate abilities' may be another determinant of BRP. Unlike motivation and personality, which are related to behaviour, innate ability relates to skills, knowledge and expertise. It is possible that these traits are the result of human capital investments, in the form of education and training (see section 6.2.2.2.1). According to Gottfredson (1998), cognitive ability refers to general intellect (also known as the 'g' factor), task specific knowledge, divergent thinking style and ideational fluency. The results of the qualitative analysis suggest that i) intelligence, ii) track record and iii) perceptiveness are key characteristics of innate ability that contribute to BRP. Each of these is now discussed.

Intelligence

Key terms such as 'bright', clever' and 'creative' were used to describe intelligence, as an ability that is inherent to the individual. This "conceptual agility" (R15) was cited frequently in conjunction with personality, indicating a potential overlap. Jensen (1998) argues that the general intelligence factor is hereditary. However, this assertion has been widely debated (Deary, Johnson & Houihan, 2009; Hernstein & Murray, 2010). The findings of this analysis suggest that human capital investments (such as education and experience) are likely significant contributors to intelligence. This is evidenced in the emergence of 'track record' as a theme related to innate ability.

Track record

Key terms such as 'competence', 'proficiency' and 'know-how' were used to describe track records of individuals who have previously attained breakthrough success. As one respondent noted, "*the best predictor of the future is often the past*" (R21). This finding suggests that individuals who have previously obtained breakthroughs or have a record of generating radical innovations are likely to produce more. This finding may be related to the composition of the sample. Several qualitative respondents (notable scientific award winners) had been awarded different prizes for different breakthroughs. As many respondents noted however,

breakthrough productivity requires a combination of innate abilities with other facilitators (such as motivation, personality and climate). This association was evidenced by the emergence of 'perceptiveness' as a sub-theme of innate ability.

Perceptiveness

Referred to as an ability to 'see the bigger picture', perceptiveness was shown to be closely related to motivation and personality. In particular, perceptiveness was linked to curiosity and conscientiousness. Key terms such as 'insight', 'intuition' and 'understanding' were used to describe individuals who are perceptive. This sub-theme also linked to notion of collaboration. Individuals who engage in cross-disciplinary collaboration, or who have cross-disciplinary interests are more likely to produced breakthroughs. This finding is strongly supported by innovation theory, which predicts increased innovation through the interaction of diverse knowledge inputs (Smith, 2010). This sub-theme also links to the notion of diverse HCI. Those individuals who have more varied forms of education, training and experience may be more likely to produce breakthroughs. Primarily, perceptiveness refers to 'big picture' thinking. Referred to as a "flat competence" (R20), the ability to understand problems from multi-disciplinary and macro perspectives was cited as a key characteristic of a breakthrough innovator.

One of the primary aims of this research is to investigate the relationship between technological propensity and productivity. In the context of this research, technological propensity refers to the extent to which individuals take advantage of technological opportunities that offer economies of scale. Examples of such technologies include the Internet and social media. Examples of methodologies that have become enabled by these technologies include crowdsourcing and crowdfunding. These technologies and methodologies are of particular interest because they offer a way to exponentially increase knowledge interactions, thereby overcoming the problem of knowledge aggregation (Smith, 2010; Callaghan, 2014a). The maximisation of knowledge interactions is likely to maximise the production of radical innovations. In the context of this research, technological propensity may be a facilitator of innovative performance, in the same way that personality, motivational values, work climate and innate abilities are facilitators of innovative performance. In the qualitative investigation of the relationship between technological propensity and productivity, a series of interlinking questions were asked to i) examine the relationship between technological propensity and BRP

and ii) to investigate the extent to which new technologies and methodologies have already been adopted, and iii) to investigate the extent to which they may support breakthrough research productivity in the future.

6.2.2.1.4 Technological propensity is related to BRP (4.4.1.4 Proposition A4: Open technological orientations are positive drivers of BRP)

Respondents were not prompted to comment on technological propensity. Rather, respondents were asked a series of questions related to 6G theory in order to assess its potential relationship to BRP. The derivation of these questions was discussed in Chapter 2 and 3, and are summarised, in Table 62 below.

Table 62: Summary of Questions relating to Technological Propensity and BRP

	Question	**Emergent themes from analysis**
1	*Do you think that journal publications that accept academic work in your field sufficiently promote innovative research in your field? Did you experience any type of resistance from the academic publishing system when trying to publish your breakthrough?*	Journal publication perception, open orientation
2	*The management of scientific research is sometimes considered counter-productive. Do you think it is necessary, or possible to try to enhance the effectiveness/efficiency of scientific research, or to try accelerating the rate at which breakthrough innovations occur? And why/why not?*	Management and acceleration, open orientation
3	*There's been a recent trend in the use of open innovation; obtaining data from large numbers of people spread across different geographical locations through the Internet and social media and smart technology. This has become very popular in health/medical research and is known as participative science. What are your thoughts on using these types of technologies to gather data in your field?*	Crowdsourcing, technology use, open orientation
4	*A lot of research faces budget constraints. Can you think of any way to streamline research funding or think of alternate methods of research funding?*	Crowdfunding

This series of questions, discussed above, forms the foundation of the investigation into technological propensity, or the extent to which individuals take advantage of new technologies and methodologies that offer significant economies of scale, such as crowdsourcing and

crowdfunding. The results of the qualitative analysis suggest that technological propensity is, in some ways, related to BRP. These findings were comprised of six interlinking sub-themes, including: i) open orientation, ii) crowdsourcing, iii) crowdfunding, iv) technology use, v) management/acceleration, and vi) journal publication perception. Each of these is now discussed, as follows.

Open orientation

As previously discussed, 6G theory is premised on the notion of open innovation (Callaghan, 2014a). Chesbrough (2003a) refers to open innovation as a new paradigm of innovation, where knowledge flows both in and out of organisations, without the impediment of organisational, geographical, political or other boundaries. Adopting open innovation means taking advantage of widely distributed knowledge which may be located outside of the organisation. Qualitative analysis revealed an underlying current of open orientation amongst the sample. In this context, open orientation means an individual-level willingness and propensity to engage with knowledge from unconventional sources. This sub-theme linked closely to sub-themes in motivation and personality, in that respondents advocated open traits such as collaboration and communication, to attain BRP. A smaller portion of the sample advocated for communication and collaboration with individuals who are not academic researchers or scientists. The sharing of scientific data is considered critical in addressing large scale problems. Many respondents noted the need to 'cast wide nets', so as to obtain as much information and knowledge as possible when addressing large problems. This 'open orientation' proved to be a considerable determinant of BRP. Most respondents agreed that closed models of innovation are generally outmoded and inefficient, particularly since the emergence of the Internet and Big Data. Several respondents emphasised the importance of improved knowledge transfer across scientific, academic and organisational boundaries. Attention was also drawn to the notion of user innovation. For example, one respondent referenced an important medical innovation related to muscular dystrophy that came from a patient. Conversely, there were some respondents who preferred to work in isolation and rejected the notion of collaboration with non-scientists. However, this portion of the sample was small.

Crowdsourcing may be seen as a form of open innovation (Brabham, 2008), albeit one that usually takes place online or, over the Internet (Howe, 2006). Like open innovation, crowdsourcing involves the interaction of diverse knowledge inputs and is therefore well suited

to producing innovations and finding solutions to problems. However, crowdsourcing differs from open innovation, in that it can occur in real-time.

Crowdsourcing

Analysis revealed a general agreement that finding solutions to large scale problems requires large scale and diverse knowledge inputs. The example provided was that of the Ebola outbreak of 2014. Most importantly, the analysis revealed a general agreement in regard to real-time solutions; that new information and communication technologies (ICT) such as the Internet are uniquely suited to aggregating knowledge inputs in near real-time. This was noted as imperative in tackling large scale problems which may produce catastrophic consequences. A large portion of the sample agreed that new advances in ICT have made such problems more manageable. The ability to communicate knowledge, information and data in significantly reduced timeframes has already seen success. Some respondents noted that the Ebola outbreak may have caused far more harm had it occurred ten years prior.

Major online crowdsourcing platforms such as InnoCentive and Mechanical Turk offer users the choice of using expert, amateur or mixed (expert and amateur) crowds to solve problems (Goodman, et al., 2013). While many respondents were supportive of expert input to address large-scale problems, many were resistant to the notion of amateur (or, civilian) input. This suggests a reluctance to incorporate non-scientific knowledge into scientific research. Granted, non-scientific knowledge is not expected to be used in scientific research. However, growing evidence from citizen science and crowdsourcing initiatives have proved its effectiveness and potential to provide fresh perspectives on old problems (Swan, 2012a; Swan, 2012b; Torr-Brown, 2013).

Previously, analysis revealed that BRP requires personalities and motivations that do not adhere to conventional modes of thinking. Independent thought and rejection of orthodoxy were cited as important drivers of BRP. However, the analysis also reveals that respondents are reluctant to trust, or willing to make use of outside sources of knowledge (i.e. crowdsourcing). This schism underlies 6G theory. Thinking ‘outside the box’ is considered a driver of BRP. Rejecting conventional wisdom is considered a driver of BRP. Failing to critically evaluate ‘expert’ knowledge is considered detrimental to BRP. However, the notion of crowdsourcing was met with disdain.

Respondents did however, agree that a greater degree of cross-collaboration, across geographical boundaries is essential to address global problems. Some referred to the usefulness of new technologies such as the Internet, which have made this possible. It was also suggested that a greater freedom of availability of knowledge and data is required to address such problems. A probing question was used to further discern the potential of crowdsourcing, but this was met with negative responses. Respondents associated the notion of crowdsourcing with 'mob mentality' and cited consequences of large collective decisions, such as the election of the present political administration in the USA. This suggests that the term 'crowdsourcing' may be viewed as a gimmick, contrived, or over-sensationslied. Previous studies have found that the use of crowdsourcing in certain industries has been met with suspicion. However, these views are generally uninformed (Linders, 2012; Griffin, 2013).

Similarly, respondents seemed reluctant to consider new forms of research funding. Almost all respondents agreed that the research funding process is bloated, overly-rigid, inflexible and insufficient. But few were able to suggest feasible alternatives.

Crowdfunding

In 2014, a KickStarter user launched a campaign to fund a "world-record breaking potato salad" (Siva, 2014, p. 384). What was initially intended as a hoax eventually raised over US$50,000 and worldwide media attention. This example may be an exception to the rule. However, it does show the potential of crowdfunding to amass financial resources in significantly reduced timeframes. Crowdfunding has been successfully leveraged to fund art, film and music projects (Bradford, 2012). More recently, crowdfunding has become an important source of financial resources for political campaigns, as well entrepreneurial startups and Small and Medium Sized Enterprise (SMEs) (Dey & Marti, 2016).

Analysis revealed that almost all respondents had experienced difficulties in obtaining research funds. Many expressed despondency and frustration with the research funding process. When prompted to list alternate forms of research funding, many suggested resorting to private funders or described how funding systems should be restructured. Despite growing evidence of the potential of crowdfunding to finance scientific research (Torr-Brown, 2013; Silva, 2014; Dey & Marti, 2016), its use seems to have not yet penetrated the upper echelons of academia.

Although no direct references to crowdfunding were made, some respondents did mention the use of 'idea competitions' to generate research funds. Idea competitions refers to an open call to solve a problem, in exchange for a reward (Stieger, Matzler, & Chatterjee, 2012). The idea of awarding research funds to new innovative ideas was also put forward. While these forms of funding may provide some relief, they do not encapsulate 6G theory, since they lack real-time capability. The issue of resource availability is discussed further in section 6.2.2.2.3.

These findings seem to suggest a significant disconnect between award-winning scientists and new technologies and methodologies. Despite their abilities as radically innovative scientists, most of the respondents in this sample dispelled unconventional methods of knowledge aggregation or research funding. Instead, some noted their preference to stick to what has worked for them in the past. Evidently, what has worked for them in the past led to their breakthrough successes. But despite describing the importance of rejecting conventional wisdom and 'thinking outside the box', the qualitative sample generally did not show interest in unconventional methods of knowledge aggregation or research funding such as crowdsourcing or crowdfunding. Despite their indifference, much of the sample did recognise the need for new technologies. Some addressed their potential applications.

Technology Use

As previously discussed, the average age of the sample was 73.5 years old. The relationship between age and technology perceptions (or, attitudes to technology) have been investigated (Lee & Coughlin, 2015, Vroman, Arthanat & Lysack, 2015). Studies have also investigated the association between age and technological fluency (Huang, Wu, Cheng & Yang, 2016). In most of these studies, samples were comprised of individuals over 65 years of age. In general terms, older individuals (over age 65) tend to have less positive attitudes to technology and are also less technologically fluent than younger individuals (Lee & Coughlin, 2015; Vroman, et al., 2015; Huang, et al., 2016).

Some respondents exhibited disinterest in using technology in their research, preferring to use the same methods that have worked for them in the past. Several respondents noted that they were computer illiterate, although these respondents only accounted for a significantly small portion of the sample. Most of the sample strongly supported the notion of using technology to

advance their own research interests. A large majority of the sample agreed that new technologies (particularly ICT such as the Internet) offer significant advantages in addressing wide-scale problems and in producing BRP. However, the manner in which these technologies can and should be leveraged and applied, and the extent of their potential, was debated.

Management and Acceleration

Following Callaghan (2014a), scientific research productivity can be significantly accelerated by the application of new technologies and methodologies such as crowdsourcing and crowdfunding. The probabilistic mechanism underlying 6G theory means that exponential knowledge and financial inputs may result in an exponentially increased probability of producing breakthrough research outputs. The more research outputs are produced, the greater the chance of radically innovative (or, breakthrough) research outputs being produced. This is a form of Accelerated Radical Innovation (ARI), a decrease in time between the production of radical innovations made possible by highly efficient management structures. An example of ARI is the production of Apple's iPod, iPhone and iPad in 2001, 2007 and 2010 respectively. If the role of management is ensuring efficiency (Thompson & McHugh, 2009; Smith, 2010), then the process of scientific research, if managed effectively, might be accelerated. Accelerated scientific research may increase the probability of producing more radical innovations. As the rate of innovative research outcomes increases, the probability of producing radical innovations will also increase.

Qualitative analysis revealed mixed perceptions related to the management of scientific research. For some respondents, management serves only to invalidate scientific progress by introducing overly-stringent rules and regulations. For others, good management can help to streamline the research process. The issue of ARI in academic research also received mixed responses. For some, scientific research cannot be accelerated. As one respondent suggests, "*a good publication is a piece of art*." Others however, noted that good management can help and guide the research process toward objectives, potentially helping to accelerating output.

In both cases, the quality of management seems to be an important differentiator. 'Good' management can help, guide and streamline the research process by maximising efficiency and effectiveness. Poor management may have the opposite effect. The sourcing of knowledge and funding and the management thereof, has now been discussed, in relation to technological

propensity and 6G theory. These are the inputs and processes required to generate BRP. As previously discussed, academic research productivity is often measured by journal publication output over time (Altbach, 2015), as was the case in this research. These are research outputs, or the outcome of the research process. Figure 34, below, depicts this process, as derived from respondent inputs.

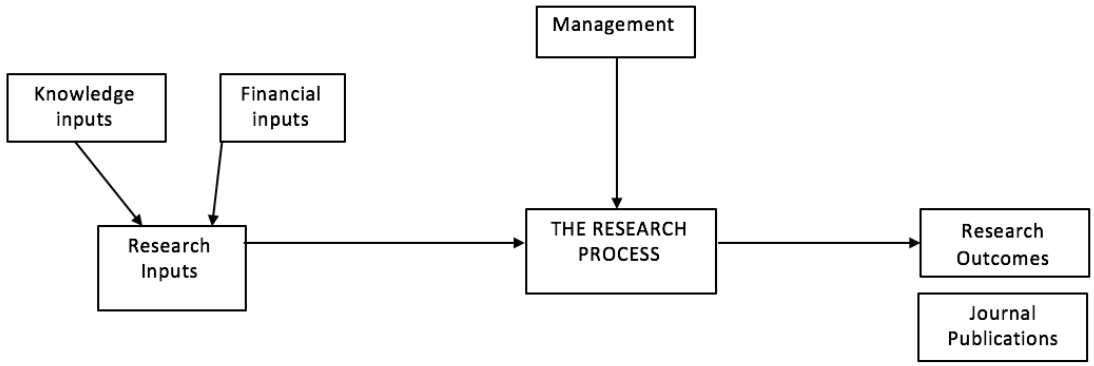


Figure 34: The research process related to technological propensity

The innovativeness of the journal publication system has been questioned (Anderson, 2004; Campanario, 2009; Bornman et al., 2010; Welsh, 2013). If academic and scientific researchers have a social obligation to produce BRP, then journal publications should encourage the publication of radical and breakthrough research. Drawing from qualitative data, an analysis of the state of scientific journal publication was conducted.

Journal Publication Perception

The analysis of journal publication perception was clustered into two categories of responses. The first of these is referred to as 'pro publication'. The respondents in this category expressed positive views towards the journal publication system. For these respondents, the journal publication system is an efficient and effective vehicle of knowledge dissemination. Furthermore, in a broad sense, the journal publication system is justified in its restrictive publication policy. Research that does not conform to research standards and norms should not be published unless it has been thoroughly vindicated. The second category is referred to as the 'anti-publication' category. These respondents suggested that, in general terms, the journal publication system is flawed because it is overly rigid and inflexible. Because of this, important

scientific breakthroughs are not published timeously, if at all. In response, many of these respondents have taken to other forms of distribution, including conferences and electronic journals. These findings suggest a dichotomous viewpoint on the issue of scientific journal publications. There does seem to be a sizeable contingent of scientific researchers that believe that the present system of publication is outmoded. Interestingly, those looking to other methods of publication have turned to new technologies. In particular, the Internet has become a popular mode of publication that allows easy access to researchers and readers alike.

Amongst the concerns regarding online publication was that of quality control. Many respondents argued that the Internet does provide an effective and efficient channel for research distribution but that it is impossible to validate. This increases the risk of misinformation, poor research and information overload. These are valid concerns as they may bring into question the repute of scientific research. The Internet does offer advantages, but the lack of any effective management structures poses numerous problems. However, this may not be necessary. As previously discussed, the accuracy of some articles on Wikipedia have been found to be as high as 99.7%, in comparison to peer-reviewed journal articles (Kränbring, et al., 2014). Wikipedia functions in a manner that is analogous to complex systems found in nature. Swarms of bees are an example of naturally occurring decentralised collectives. Swarms can solve complex problems without individual bees having full knowledge of the problem at hand. Each bee uses specialised skills and knowledge to fulfill small tasks. Once tasks are completed, the swarm is alerted. Other members of the swarm apply their own specialised skills and knowledge, until the problem space is eroded, and the problem is solved. Like swarms of bees, Wikipedia users need not possess full information of a given topic. Instead, each user contributes their own specialised knowledge (Garnier, et al., 2007; Rosenberg, 2016). Other users incrementally build on this input until a full article is developed. Specialised knowledge interacts organically, eliminating errors and continually improving until a point of saturation is reached. In this way, thousands of people contribute to a single article. Essentially, online swarms of people form their own decentralised management structures, to ensure validity and quality control. The risk of misinformation is still possible, but less so than if Wikipedia was managed by a central authority (Maehre, 2009).

These types of decentralised systems may provide an opportunity for the publication of academic and scientific research. Given the high degree of ‘anti-publication’ (respondents that were critical of the rigidity and inflexibility of the journal publication system) amongst the

qualitative sample, and the gradual shift towards new methods of publication, it is suggested that new models should be investigated. It is argued that the Wikipedia model described above, represents a potential future complement to journal publication. This model is not recommended as a replacement to traditional systems of journal publication but may offer a useful alternative channel of publication. It may also enhance the rate at which innovative research is disseminated. Assessing the potential of such a system is beyond the scope of this research. However, it does present an opportunity for future research. Having discussed the findings of the qualitative analysis related to internal drivers of BRP, a discussion of the external drivers of BRP now follows.

6.2.2.2 Proposition B: External Drivers are related to BRP (External Drivers such as human capital investments, work climate and resource availability are positive drivers of BRP)

External drivers refer to peripheral influences which may impact on an individual's productivity. Unlike internal drivers which are inherent to the individual, external drivers are 'outside' stimuli, which are usually controlled by groups of people, rather than by individuals. To assess the determinants of BRP, respondents were asked what they thought were important external influences that would enable the production of breakthrough research. Responses generally fell into three broad categories. These include i) human capital investments, ii) work climates and iii) resource availability. Each of these is now discussed in relation to BRP, as follows.

6.2.2.2.1 Human Capital Investments (HCI) are related to BRP (Human Capital Investments in education, experience, support and cross-pollination are positive drivers of BRP)

Human Capital Investments (HCI) refer to the investment of resources that contribute to the development of an individual (Bosma, van Praag, Thurik & De Wit, 2004). Examples include education, experience and on-the job training. Although HCI are intangible, they are still considered external drivers of BRP. This is because HCI are the product of external influences. To gauge the extent of respondents' HCI, the following question was asked:

Was there anything specific in your background – experience, education, training - that contributed to your breakthrough work? How do you think your prior experience contributed to your (biggest/major) breakthrough?

Responses to this question generally related to 3 categories, or sub-themes related to HCI. These include i) education and experience, ii) support and iii) cross-pollination.

For Becker (1994, p. 17), "education and training are among the most important investments in human capital." All respondents in the qualitative sample were highly educated. All respondents had obtained a PhD. Most of the respondents had attended Ivy-League (or equivalent) colleges and universities. Almost all respondents cited their early education (including primary and high schooling) as important precursors to their later successes. Early social support was also cited as an important precursor. This includes support from parents, siblings, other family members, friends and teachers. Many respondents noted that having freedom to explore at a young age is an essential stimulator of curiosity. Respondents also cited the importance of university or college education and training. Many respondents cited the importance of building strong educational foundations.

Interestingly, the *diversity* of these types of HCI were also found to be important contributors to later success. In several cases, respondents suggested that occasional change of focus, or change in education, enabled them to see things from new and different perspectives. Moving from one country to another, or from one university or college to another, was seen as a positive stimulus that could bring about innovative change. Changing one's area of focus from one field to another was also frequently cited as an important turning point. Some of these focus changes occurred in similar fields, others in entirely different fields. However, respondents that reported having experienced such change were primarily female or from developing (rather than developed) countries.

This finding suggests that HCI diversity is a contributor to BRP. Individuals who have acquired *varied* education, training and experience may be more likely to produce radically innovative outputs. This finding is consistent with innovation theory. For Smith (2010), innovation is the result of the interaction of diverse knowledge inputs, at the level of the collective (i.e. the group or organisation). However, these findings suggest that the same concept applies at the level of the individual. The interaction of diverse accumulation of education, training and experience

may help in developing innovative minds, over time. It is unknown whether the innovations produced by such individuals are of higher quality than those produced by individuals with more traditional HCI. This presents an interesting opportunity for further research. It may therefore be possible that HCI diversity mediates the relationship between external drivers and BRP.

Another important sub-theme related to HCI is that of cross-pollination. Key terms such as 'multi-disciplinary', 'cross-discipline and 'perspective' were used to describe the interactions of knowledge and information that leads to innovation. Like HCI diversity, this suggests that the interface between different sources of knowledge should be minimally restrictive and maximally flexible as possible, to allow the free flow and exchange of ideas and information. This sub-theme links to previous qualitative findings of collaboration, communication, cooperation and cross-disciplinary interaction. While some respondents suggested that they preferred to work alone, the findings of this analysis seem to suggest that innovation (and particularly radical innovation) cannot occur in a vacuum.

Management plays an important role in stimulating innovation. By stimulating motivational drivers and interactions, management can control and implement research environments, or 'work climates' that are conducive to BRP.

6.2.2.2.2 Work climate is related to BRP (Work climates that encourage collaboration and provide incentive and managerial support are positive drivers of BRP)

Work climate refers to "organisational setting" (James, et al., 1978, p. 783). This is differentiated from work climate perception, which is and organisational setting that is "expressed in terms that reflect psychologically meaningful interpretations of the situation." To investigate the relationship between work climate and BRP, respondents were asked the following question:

> *"In your experience, what are the characteristics of a work climate that is conducive to attaining a research breakthrough?"*

Four key sub-themes related to work climate were identified. These include i) freedom, ii) incentive, iii) collaboration and iv) managerial support. Freedom relates to both academic and

financial freedom. Patterson, et al. (2005) argue that work climates that promote flexibility, outward focus and reflexivity are more inclined to produce innovations. (i.e. Open Systems models (OSM)). The findings of the qualitative analysis seem to support this argument.

The attainment of BRP requires freedom to explore new ideas which may be unconventional, and freedom to pursue research objectives without financial constraints. Analysis also revealed that bureaucratic restrictions and boundaries may inhibit the pursuit of BRP. Removing these limitations may enhance breakthrough productivity. In other words, flexibility is a key characteristic of a work climate conducive to producing research breakthroughs.

Incentive was cited as a potential driver of BRP. Like motivation, both intrinsic incentives (such as recognition) and extrinsic incentives (such as financial compensation) were revealed to be effective. However, it was generally agreed that intrinsic incentives produce superior results. Work climates that encourage innovation through reward structures, either extrinsic or intrinsic, are more likely to produce breakthroughs.

Work climates that encourage collaboration are also considered more likely to produce breakthroughs. Following the OSM model (Patterson, et al. 2005), this would entail a work climate that promotes an outward focus. Climates that promote cross and multi-disciplinary collaboration across faculties and across institutions, is likely to produce innovative research. Interestingly, no mention of collaboration with non-scientific entities was made. This finding supports previous findings related to technological propensity. Non-scientists (or, citizens) are generally not considered as potential scientific collaborators, despite research that suggests that new methodologies such as crowdsourcing (Swan, 2012) and citizen science (Torr-Brown, 2013) may improve the probability of producing breakthroughs.

Managerial support was cited as perhaps the most important characteristic of innovative work climates. Efficient managerial structures should be able to allow freedom, provide incentive and encourage collaboration. By exercising control in these areas, management can foster innovation and increase the probability of producing breakthroughs. Essentially, management structures that are reflexive, or adaptable to environmental change, are more likely to create climates in which breakthrough productivity is enabled.

For Patterson, et al (2005), open systems model (OSM) climates are better at producing innovation than internal process models (IPM) climates. The findings of the qualitative analysis seem to support this contention. Work climate was also found to be closely related to resource availability. In order to ensure climates that are in line with OSM, management structures also need to allow for a free flow and easy access to resources, both financial and otherwise.

6.2.2.2.3 Resource availability is related to BRP (Availability of Resources, financial freedom and a reduction of bureaucracy are positive drivers of BRP)

Although no question related to resource availability was posed, respondents often went to lengths to decry a lack of resources, particularly financial resources, or research funding. This sub-theme emerged in relation to the question on alternative methods of research funding. Respondents frequently described situations in which research funding is scarce and grant application procedures are overly complicated, exclusive and long-winded. Despite this, there were no references to crowdfunding as a potential method of research funding. Some respondents mentioned incentive schemes and reward programs. Approaching private funders (individuals or organisations outside the university) was also listed as a potential method of generating research funds. This finding seems to suggest that, of the qualitative sample (highly esteemed and award-winning scientists), there is little awareness of, or interest in, crowdfunding to fund scientific research, despite research that suggests that crowdfunding offers a viable alternative to traditional methods of funding (Stiegler, et al, 2012; Dey & Marti, 2016; Palmer & Verhoeven, 2016). If technological propensity represents an individual's proclivity to seize new opportunities related to technologies and methodologies that offer scale advantages, then this finding suggests a low technological propensity amongst the qualitative sample of this study. There may exist significant unexploited opportunities, in the form of crowdfunding to generate resources. These findings also suggest that the traditional, 'closed' model of research funding has reached its natural limit, or S-Curve (Foster, 1986). For Christensen (1997), organisations are often too late to adopt new modes of innovation, and as a result, often lose competitive advantage. If the same can be said to apply to the evolution of new models of research funding, these findings suggest that research funding is often still constrained by old, closed models of funding, despite evidence of the emergence of a new model, in the form of crowdfunding.

Some respondents also referred to other resources such as lab equipment and lab and research assistants. Time is another resource that seems to be in short supply. Respondents noted that time constraints have detracted from their research productivity. Managing time more efficiently may help reduce time stresses. Time constraints however, are generally considered unavoidable. In summary, these findings suggest that resource constraints, both financial and otherwise seem to inhibit BRP. However, previous research suggests that financial constraints to scientific research may be overcome through the use of crowdfunding (Palmer & Verhoeven, 2016).

6.2.3 Proposed moderating and mediating relationships

The findings of the qualitative analysis suggest that there exist certain moderating and mediating relationships between variables. These are summarised in Table 62, below.

Table 62: Proposed moderating and mediating relationships derived from qualitative analysis

	Proposed moderating and mediating relationships
1	Gender moderates the relationship between technological propensity and BRP
2	Nationality moderates the relationship between technological propensity and BRP
3	Field of study moderates the relationship between technological propensity and BRP
4	HCI diversity moderates the relationship between external drivers and BRP
5	Technological propensity mediates the relationship between personality and BRP

The proposed moderating and mediating relationships in Table 62, above, seem to reflect the theoretical model derived from the literature, which were tested quantitatively. Having concluded discussion regarding the primary qualitative findings, the quantitative findings are now reviewed, as follows.

6.3 DISCUSSION OF QUANTITATIVE FINDINGS

The findings of the quantitative analyses are now discussed, in relation to literature. The findings of both the academic researcher (AR) and crowd-worker (CW) samples are reviewed. Since the focus of this research is productivity in the context of academic research, it is stressed that the findings of the AR analysis are the primary focus of this discussion. The findings of

the CW analysis are used primarily as a comparative measure. This section is structured according to the research questions and hypotheses derived from the literature. Research Question A is discussed first, as follows.

6.3.2 Research Question A: What is the relationship between technological propensity and productivity?

The relationship between technological propensity and productivity was investigated for both the AR and CW samples. The dependent variable, 'productivity' differs according to the sample. For the AR sample, productivity was measured by a total of published journal articles over number of years' experience as an academic researcher. This ratio is referred to simply as 'productivity' For the CW sample, productivity was measured by the number of completed MTurk HIT's over the number of years' experience as an MTurk worker (MTurker). This ratio is referred to as 'crowd-worker productivity (CWP). Technological propensity is a measure that was derived from the literature. While the wording of the technological propensity scale used in questionnaires differs slightly according to sample, the measurements of technological propensity constructs are the same. The technological propensity measure comprises of five underlying constructs, including: i) tolerance for disruption, ii) technology use, iii) open orientation, iv) crowd propensity and v) collaborative propensity. The relationships between technological propensity, its' underlying constructs and productivity were examined. Tests of correlation were conducted. Thereafter, tests of regression were conducted to test the hypotheses. Each of these is discussed, as follows.

6.3.2.1 Hypothesis A1: Technological propensity is significantly associated with productivity

For both the AR and CW samples, it was found that the overall measurement of technological propensity is not significantly associated with academic research productivity (.077; p<.115), nor with CWP (002; p<.964). This finding suggests that the extent to which both academic researchers and crowd-workers take advantage of new technological and methodological opportunities is not related to their productivity. Further tests of correlation between the five constructs of technological propensity, productivity and CWP were conducted, to provide further insight into this finding.

For both the AR and CW samples, it was found that tolerance for disruption, technology use and open orientation are not significantly correlated with productivity, nor CWP. In other words, the extent to which individuals are able to tolerate, make use of, or are open to new technological or methodological advancements, is not significantly associated with work productivity.

It may be possible therefore, that in both AR and CW contexts, work processes are, to some extent, immune to the influence of certain new technological or methodological advancements. Indeed, in the context of academia, it has been argued that academic research processes may often adhere to strict paradigmatic conformity, where traditional procedures are followed strictly (Alvesson & Sandberg, 2013), and unconventional modes of productivity are not frequently adopted (Hanson, 1990; Campanario, 2009; Bornman, et al., 2010). Thus, academic researchers may seek to avoid incorporating the use of new technologies and methodologies to improve productivity.

It may be possible that the same routinisation has occurred in the CW context, however this may a desired outcome. As previously mentioned, the crowd-workers sampled in this research include MTurk workers only. Crowd-workers operating on other 6G platforms (such as InnoCentive or Wikipedia) may differ substantially. On MTurk, crowd-workers complete brief and relatively simple HITs, within a set time frame, and are paid for each of their contributions (Goodman, et al., 2013). In this context, it may be possible that new technological or methodological advancements are not needed to enhance work performance, or productivity because MTurk is designed so that crowd-workers produce at maximum efficiency (Litman, et al., 2017). Indeed, it has been noted that MTurk work is primarily geared toward efficient and effective work output in as little time as possible (Ipeirotis & Horton, 2011; Casler, Bickel & Hackett, 2013), rather than creativity and innovation (Litman, et al., 2017).

In the CW analysis, it was found the crowd propensity, or the extent to which an individual would make use of crowdsourcing or crowdfunding to improve their productivity, is not related to CWP. This is expected, since MTurk is designed to produce output efficiently and quickly (Callison-Burch & Dredze, 2010; Goodman, et al., 2013). In the AR analysis, it was found that crowd propensity is significantly, but negatively correlated with productivity (p= -.162). Academic researchers that are likely (or willing) to engage in or adopt crowdsourcing and/or crowdfunding, may produce less output than their peers, who reject the use of crowdsourcing

and/or crowdfunding. This finding may be attributable to the argument of routinisation (King & Anderson, 2002; Anderson, et al., 2004) in academic research, particularly in journal publication. Alvesson and Sandberg (2013) suggest that academic researchers that adhere to the 'tried and tested' are more likely to get published than others who seek to innovate and introduce new ideas. This finding seems to support this assertion, since those academic researchers that reject crowdsourcing or crowdfunding seem to have published more research output than those that would be willing to adopt crowdsourcing or crowdfunding. It is argued that research output that does not conform to formalised standards and procedures may often be rejected out of hand (Campanario, 2009; Bornman, et al., 2010; Welsh, 2013). The willingness, or propensity to engage in or adopt the use of crowdsourcing or crowdfunding, may be reflective of individuals who tend to reject convention, and are therefore published less frequently than their peers.

It was also found that for academic researchers, collaborative propensity (or, the extent to which an individual is likely to collaborate with others to improve their productivity) is significantly correlated with productivity (p= .230). This finding is strongly supported by literature (Landry, Traore & Godin, 1996; Lee & Bozeman, 2005; Ponomariov & Boardman, 2010) and the findings of the qualitative study. Collaboration, particularly cross-disciplinary collaboration may lead to the cross-pollination and communication of ideas and knowledge (Lee & Bozeman, 2005; Bajark & Robinson, 2008), which may enhance research productivity (Abramo, D'Angelo & Di Costa, 2009). For the CW sample however, collaborative propensity was found to be significantly, yet negatively correlated with CWP (p= -.087) Although crowd-work entails the collaboration of large numbers of people, some forms of crowd-work (particularly MTurk) requires little to no interaction with other crowd-workers (Kittur, 2010; Goodman, et al., 2013). Therefore, those individuals who prefer crowd-work to other forms of work (and therefore have lower collaborative propensities) may be more likely to spend more time working on MTurk, resulting in higher CWP.

Based on these analyses, it can be concluded that overall technological propensity is not significantly associated with productivity, in both the AR and CW samples. However, in the case of the AR sample, it was found that academic researchers that are more likely to collaborate may produce more research output. This finding is in line with the findings of previous studies that investigate publication productivity (Sooryamoorthy & Shrum, 2007; Ynalvez & Shrum 2011). Interestingly, in the AR analysis, it was discovered that individuals

with high levels of crowd propensity (or, the extent to which individuals are likely to employ crowdsourcing and crowdfunding for their research) are *less* research productive. In the CW sample however, it was found that crowd workers that are more inclined to collaborate are less productive. In conclusion, some of the constructs of technological propensity may be associated with productivity and CWP. However, technological propensity (as an average) is not significantly associated with productivity and CWP. Certain implications arise from these findings.

First, these findings imply that technological propensity, or the proclivity to seize opportunities related to new technologies that offer economies of scale, is unrelated to productivity. Second, because of the negative correlation between crowd propensity (the willingness to use crowdsourcing and crowdfunding to improve research productivity) and productivity, technological propensity may, at some levels, be negatively associated with productivity. Individuals with higher 'crowd propensities', seem to produce less research output. This may suggest that such individuals, who are more open to novel processes, experience high levels of rejection and resistance from journal publications (Campanario, 2009; Bornman, et al., 2010). This finding is also supported by the results of the qualitative analysis. Third, for the AR sample, collaborative propensity was found to be significantly correlated with productivity. This means that the tendency to collaborate may result in higher levels of productivity. However, in the 6G space, crowd-workers are more productive when they are *less* collaborative. This shows an important differentiation between academic and 6G spaces. Having discussed the results and implications of the testing of Hypothesis A1, Hypothesis A2 is now discussed, as follows

6.3.2.2 Hypothesis A2: Personality is significantly associated with technological propensity

Following the FFM model of personality, which comprises i) openness to experience, ii) extraversion, iii) conscientiousness, iv) neuroticism and v) agreeableness, (Costa & McCrae, 1990), five separate quantitative tests were conducted for each sub-hypothesis of Hypothesis A2. These tests were conducted to test the association between personality and technological propensity. The results of the testing of this hypothesis are now discussed for each factor of the FFM model, and for both the AR sample and the CW sample, as follows:

6.3.2.2.1 Openness to Experience is significantly associated with technological propensity.

In both the AR and CW samples, openness to experience was shown to be positively, significantly associated with technological propensity. (For the AR sample, .127; p<.010 and for the CW sample, .316; p<.000). This finding is supported by literature. According to Chesbrough (2003a), openness breeds innovation, at the level of the organisation. It would therefore be expected that this characteristic may trickle down to the individual level, since openness at both the individual and organisational levels has been found to associate with heightened levels of innovativeness (Salter, Wal, Criscuolo & Alexy, 2015). Open individuals may therefore be considered more likely to adopt new technologies and methodologies which are founded on the principles of openness (i.e. 6G-type technologies such as crowdsourcing) (Callaghan, 2014a). However, crowd-workers were shown to have a significantly stronger association between openness to experience and technological propensity. Furthermore, in the case of crowd-workers, openness to experience was found to be correlated with tolerance for disruption (p = .257), crowd propensity (p = .295) and open orientation (p = .174). However, this was not the case for academic researchers. Collaborative propensity was shown to be associated with open orientation in academic researchers (p = .106), but this association was slightly stronger in crowd-workers (p = .193) This implies that individuals operating in the 6G space may be more open to experience, which in turn enhances technological propensity. However, this finding also seems to support the notion that there may exist some systematic constraints to innovation, in the AR context (Anderson & West, 1998; Campanario, 2009), which may inhibit academic researchers from adopting new modes of productivity. These constraints may diminish openness to experience and thus, technological propensities (or the extent to which individuals take advantage of new technological and methodological opportunities). Those individuals operating without such constraints (i.e. crowd-workers) may tend to be more open to experience, and therefore more likely to engage in and adopt new technologies and methodologies.

6.3.2.2.2 Extraversion is significantly associated with technological propensity.

The results of both the AR (p = .127) and CW (p = .446) analyses show that extraversion is correlated with collaborative propensity. Individuals who are outgoing, assertive, energetic and active (McCrae & John, 1992), are more likely to collaborate, or work with others. These

findings also show that for academic researchers, extraversion is not significantly associated with technological propensity (.024; p<.625). However, extraverted crowd-workers may be more likely to adopt novel modes of productivity (.375; p<.000). These differences between samples may be attributable to contextual differences. In the AR context, being enthusiastic, outgoing and energetic (i.e. extraverted) may reflect a desire to interact with other individuals in the academic research space. Indeed, as previously discussed, extraversion is also found to be correlated with collaborative propensity. However, if the academic research space is constrained by routinisation (Campanrio, 2009; Bornman, et al., 2010), then extraverted academic researchers with high collaborative propensities, may become increasingly exposed to tradition and orthodoxy. If these individuals tend to internalise this exposure, they may in turn also become increasingly traditional and orthodox. Specht, et al. (2011) suggest that openness decreases as age increases. Similarly, extraverted academic researchers may become less open to new ideas as they become further exposed to a system which may be inherently closed and routinised (Anderon, et al., 2004). In other words, technological propensity may be a function of other individuals in the environment. Conversely, in the crowd-work context, individuals who are extraverted may be more likely to be exposed to other individuals in the 6G space, who have high technological propensities. As crowd-workers interact with other crowd-workers, they may begin to internalise the features of the system within which they operate. Thus, continued exposure to may lead to increased technological propensity and such individuals may become more open to new modes of productivity.

6.3.2.2.3 Conscientiousness is significantly associated with technological propensity.

Testing the relationship between conscientiousness and technological propensity produced different results for each sample. Conscientious individuals are often described as 'disciplined' and often prefer planned, rather than spontaneous behaviour (McCrae & Costa, 1989). This trait may therefore act as a detriment to technological propensity, which would require individuals to be more open, free-thinkers and impulsive in the adoption of new technologies and methodologies, outside of traditional norms (Callaghan, 2015a). However, mean levels of conscientiousness were higher in crowd-workers (mean = 5.28), than in academic researchers (mean = 4.64). Social desirability scores (Hagighat, 2008) indicated no significant difference in social desirability between the AR and CW sample. For the CW sample, conscientiousness was found to be significantly and positively associated with technological propensity (.128; p<.002). This suggests that those individuals operating in the 6G space may recognise the

importance of new technologies and methodologies to enhance their work output. This may be because conscientiousness is associated with being efficient, organised, responsible and thorough (Costa & McCrae, 1990). Thus, conscientious crowd-workers may realise the importance and potential of new modes of productivity and pursue them to enhance their own productivity in a conscientious manner. Conscientious academic researchers however, are more likely to adhere to traditions, conventions and norms when producing research output (.037; p<.457). These individuals may therefore be more likely to pursue standard modes of productivity. Again, these findings seem to indicate significant differences in the contexts of the AR and CW samples. In the 6G space, there may tend to be a trend towards openness and an acceptance of new modes of productivity to obtain objectives. Conversely, in the AR space, there seems to be a trend focused on following standard and traditional procedures to obtain objectives.

6.3.2.2.4 Neuroticism is significantly associated with technological propensity.

The analyses indicate a negative association between neuroticism and technological propensity, for both samples. For the AR sample, (-.105; p<.034) and for the CW sample (-.244; p<.000). This finding is also supported by the results of the qualitative analysis. Neurotic individuals may be less likely to take advantages of new technologies and methodologies to improve productivity. Conversely, those individuals who are 'emotionally stable' and who are independent thinkers (i.e. those who are not neurotic) (McCrae & Costa, 1989), may be more likely to have higher technological propensities. This finding may link to the notion of absorptive capacity or, the ability to recognise and assimilate new information (Cohen & Levinthal, 1990). Neuroticism may act as an impediment to an individual's ability absorb and expand on new information, knowledge or ideas, effectively decreasing technological propensity. Therefore, it would be expected that neurotic individuals may inadvertently prefer to operate within the confines of what they already know. Such individuals would be expected to prefer not to try new methods of enhancing work output. Neurotic individuals are described as tense, worrying, self-conscious and anxious (Costa & McCrae, 1990; McCrae & John, 1992) and thus, a negative association with technological propensity is expected. These findings suggest that this negative relationship is indeed present, although to a greater extent amongst crowd-workers, than academic researchers. It can be concluded therefore, that in the 6G space, neurotic individuals may be less likely to make use of new

technologies and methodologies to enhance their productivity. Furthermore, in the context of academic researchers, there may exist a general lack of awareness of new technologies and methodologies (i.e. crowdsourcing and crowdfunding). Academic researchers who are neurotic are also less likely to adopt new technologies and methodologies, but the influence of academic research routinisation (Dewald, Thursby & Anderson, 1986; Bornman, et al., 2010), may further weaken this relationship.

6.3.2.2.5 Agreeableness is significantly associated with technological propensity.

The results of the AR analysis suggest that agreeableness is not associated with technological propensity (-.021; p<.680). This is expected since individuals that are independent minded and who embrace novel techniques and methodologies, rather than conforming to traditional norms (i.e. not agreeable), are more likely to have higher levels of technological propensity. This finding was also supported by the qualitative analysis. However, in the 6G space, it was discovered that agreeableness is significantly associated with technological propensity (.353; p<.000). Agreeable individuals are described as trusting, kind and sympathetic (Costa & McCrae, 1990; McCrae & John, 1992). Therefore, agreeable individuals are more likely to engage in and adopt new ideas based on trust or good faith. Such individuals display a willingness and eagerness to accept new ideas (Wang & Yang, 2007) without being overly-concerned regarding capabilities or potential drawbacks. Academic training however, generally disavows agreeableness in favour of more analytical type-thinking and skepticism (Campanario, 2009; Waller, 2010) of the new and untested (King & Anderson, 2004; Campanario, 2009). This finding therefore seems to support the notion of academic research routinisation (Dewald, Thursby & Anderson, 1986); that academic research has, in some cases become overly reliant on certain paradigms (Pfeffer, 1993; Bornman, et al., 2010) and resistant to change (Anderson, et al. 2004). It also highlights an important division between academic and 6G-based thought. Although critical thought is imperative to academic research (Waller, 2010), it may in some cases diminish the true potential for breakthroughs and radically innovative advancements (Campanario, 2009; Bornman, et al., 2010). This is the crux of academic research routinisation (Dewald, Thursby & Anderson, 1986; Anderson, et al., 2004). However, the abovementioned findings suggest that in the 6G space, a slight alleviation of this rigidity may provide a way to overcome this problem.

In summary, academic researchers who are open to experience may be willing to adopt novel modes of productivity. Academic researchers who are neurotic or agreeable may be less likely to do so. Extraverted academic researchers may be more likely to collaborate, but this does not necessarily imply higher technological propensity. Crowd workers who are open to experience, extraverted, conscientious and agreeable may be more likely to adopt new modes of productivity. Like academic researchers, crowd-workers who are neurotic may be less likely to do so. A discussion pertaining to the association between motivational values and technological propensity now follows.

6.3.2.3 Motivational Values are significantly associated with productivity

For Schwartz (2012), the higher order motivational values include i) self-transcendence (comprising of universalism and benevolence), ii) conservation (conformity, tradition and security), iii) openness to change (self-direction and stimulation) and iv) self-enhancement (power, achievement and hedonism). Each of these is now discussed respectively, in their association to technological propensity, in terms of both the AR and CW analyses undertaken in this research.

6.3.2.3.1 Self-Transcendence is significantly associated with technological propensity.

Self-transcendence is related to universal and benevolent motivations (Schwartz, 1992). According to the findings of this analysis, both academic researchers (.180; p<.000) and crowd-workers (.228; p<.000) that are motivated by self-transcendence are more likely to adopt new modes of productivity. This finding is also supported by the results of the qualitative analysis. It is argued that this association may be attributable to the 'prosocial' nature of work productivity. Grant (2008, p. 48) argues that some forms of work productivity may be positively related to prosocial motivations, or "the desire to benefit other people." In other words, the desire to perform one's job well may be related to universal or benevolent motivations. Furthermore, if academic researchers do indeed have an obligation to produce research outputs that address the needs of societal stakeholders (Jaffe, 1989; Radder, 2010), then the adoption of new modes of productivity may enable the fulfilment of these desires and motivations. This would only be the case if these new modes of productivity were capable of improving productivity. One example of this would be open access publication (Gargouri, et al., 2010), which may lead to an increase in the amount of radically innovative research

published (Callaghan, 2014a; 2015a). Consequently, the probability of the dissemination of radically innovative research that addresses important social problems may also increase, thereby fulfilling these proposed social obligations. Thus, it is argued that technological propensity (or, the proclivity to seize new technological and methodological opportunities) may also represent an indication as to the extent to which academic researchers seek to fulfil societal obligations, to produce radically innovative research (Jaffe; 1989; Radder, 2010; Callaghan, 2014a). Indeed, others have echoed the assertion that there is a need for more academic research that addresses important social problems (Begely & Ellis, 2012; Cummins, et al., 2014; Wu, 2017). Thus, this finding seems to suggest that individuals that tend towards self-transcendental, humanistic and benevolent motivational values are also more likely adopt new technologies and methodologies that offer scale advantages and that may subsequently offer a way to find solutions to some of these societal problems. In other words, individuals who wish to bring about positive universal change are also more highly open to adoption of new technologies and methodologies that could potentially bring about such change. This also suggests that some academic researchers may seek to reject 'tried and tested' or traditional methods of academic research and essentially transcend the barriers to breakthrough productivity.

It is interesting to note, however, that these associations generally tended to be stronger in the crowd-worker sample. This may suggest that improvements can be made in the context of academic research. If some of the processes of academic research were to be transposed to the 6G space (for example, open access publication and the use of crowdsourcing to aggregate and analyse data), it may be possible that academic researcher motivational values would shift to those that are more self-transcendental in nature. This may in turn effectively enhance the willingness the engage with and adopt new modes of productivity which may ultimately bring about solutions to social problems, thereby fulfilling obligations to societal stakeholders (Radder, 2010).

6.3.2.3.2 Openness to Change is significantly associated with technological propensity.

In both AR (.316; p<.000) and CW (.265; p<.000) samples, openness to change is positively associated with technological propensity. Openness to change relates to self-directing and stimulation motivations (Schwartz, 1992). Individuals who are motivated by self-direction tend to be independent thinkers, action-oriented and tend to seek creativity and exploration.

Similarly, stimulation refers to motivation driven by excitement, novelty and challenge (Deci, 1976; Schwartz, 1992). Academic researchers who are open to change may therefore be willing to explore outside of the boundaries or traditional norms of academic research, which may result in a higher level of technological propensity. Since openness to change is associated with exploration, learning, creativity and an interest in the novel and unconventional (McCrae & John, 1992; Bates & Khasawneh, 2005), it would be expected that academic researchers who are open to change may be more likely to explore new and different avenues, which may lead to new domains of breakthrough research. This association is slightly stronger in the 6G space (i.e. for crowd-workers). This finding may be attributable to contextual differences between academic and 6G spaces. It may be possible that the 6G space may be more conducive to motivations configured to exploration and openness than the academic research context. Again, this finding suggests that if certain academic research processes were to be transposed to the 6G context, that this may result in a change in motivational configurations, and thus perhaps a change in technological propensity.

6.3.2.3.3 Conservation is significantly associated with technological propensity.

For the AR sample, conservation is found to be significantly and negatively associated with technological propensity (-.242; p<.000). However, for the CW sample, conservation is found to be significantly, positively associated with technological propensity (.112; p<.006). The difference in these results shows significant differences in the academic and 6G spaces. In the academic context, this result is expected, since conservation is associated with values configurations that favour tradition and security (Schwartz, 1992). Both of these are antithetical to the open philosophy of 6G (Chesbrough, 2003a; Callaghan, 2014a). However, the result of the CW analysis suggests that in the 6G space, the adoption of new modes of production is considered a secure and traditional method of work productivity. This suggests that for crowd-workers, the adoption of new technologies (i.e. working on MTurk) may ensure high levels of productivity. New and unconventional technologies or methodologies can be adopted without concern regarding paradigmatic adherence. In the academic space however, adopting new technologies, methods or modes of productivity may still be considered highly risky. Indeed, it has been argued that academic research has in some cases become highly routinised (Anderson, et al., 2004). The adoption of new modes of productivity may therefore be disavowed in the academic space, in favour of long-standing, traditional methods (Waller, 2010). This differentiation suggests that new technology and methodology adoption in the

academic space is perhaps may still be mitigated by paradigmatic constraints (Pfeffer, 1993; Waller, 2010; Campanario, 2009). Adherence to convention may be expected and promulgated by a system of innovation 'gatekeepers' (Bornman, et al., 2010). Thus, methods and technologies that may be unconventional may be ignored or cast aside, in favour of those that fit traditional paradigms (Campanario, 2009; Bornman, et al., 2010).

6.3.2.3.4 Self-Enhancement is significantly associated with technological propensity.

Self-enhancement relates to motivation driven by power, achievement and hedonism (Schwartz, 1992). It would be expected therefore, that self-enhancement may be positively associated with technological propensity, since the adoption of some new technologies and methodologies may offer the means to improve productivity, thereby satisfying the motivation to achieve. However, it is also possible that self-enhancement may not be associated with technological propensity, since these same new modes of productivity may offer outcomes that are universal and humanistic, rather than those that are self-serving.

For academic researchers, the negative correlation between collaborative propensity and self-enhancement ($p = -.120$) is supported by the results of qualitative analysis, which found that more self-centered values configuration (such as power, achievement and hedonism) are not expected to be associated with a willingness to collaborate. This is also supported by theory; Schwartz (1992; 2006) suggests that individuals that seek self-enhancement are less likely to seek to exchange and share ideas and knowledge with others. According to the results of the crowd-worker analysis, self-enhancement is positively associated with technological propensity (.255; $p<.000$). This suggests that in the 6G space, the adoption of new technologies and methodologies used to enhance productivity is considered synonymous with self-enhancement. Amongst academic researchers however, self-enhancement was found to be negatively correlated with technological propensity, but not associated with technological propensity (-.009; $p<.863$). This differentiation may be attributable to differences in the nature of productivity in the academic and 6G spaces. For crowd-workers on MTurk, the pursuit of productivity is expected to be primarily self-serving (i.e. for monetary reward). However, for academic researchers, the production of academic research is more likely to be associated with a humanistic, benevolent and a world view approach (i.e. self-transcendentalism) (Grant, 2008). Indeed, it has been suggested that academic researchers have an obligation to societal stakeholders (Jaffe, 1989; Grant, 2008; Radder, 2010) to produce research output that addresses

the needs of society. Therefore, while some academic research may be conducted in the interest of self-enhancement (Laband & Beil, 1999; Grant, 2008), this finding suggests that academic research is more likely to be conducted to fulfill self-transcendental motivations. By contrast, crowd-work on MTurk may be primarily self-serving in nature (Kittur, 2010).

In summary, academic researchers who are motivated by self-transcendence and openness to change are more likely to adopt new modes of productivity, specifically those associated with significant scale advantages (such as crowdsourcing and crowdfunding). Those motivated by conservation however, may be less likely to do so. Crowd-workers who are motivated by self-transcendence, openness to change, conservation and self-enhancement are likely to adopt new modes of productivity. A discussion pertaining to the relationship between work climate perceptions and technological propensity follows.

6.3.2.4 Hypothesis A4: Work Climate is significantly associated with technological propensity

According to Patterson, et al. (2005), there are four broad categories of work climate perceptions, together comprising the Organisational Climate Model (OCM). For the purpose of this study, two opposing categories were selected for analyses. These included i) the Internal Process Model (IPM) and ii) the Open Systems Model (OSM). The IPM comprises of climate characteristics including i) formalisation and ii) tradition. The OSM comprises of climate characteristics including i) reflexivity, ii) flexibility and innovation and iii) outward focus. Both types of climates are now discussed, relation to technological propensity. Since most MTurk users tend to work from home (Goodman, et al., 2013), crowd-worker climate perception was not measured. Instead, the results discussed below relate to the academic researcher sample only.

6.3.2.4.1 Internal Process Model Climate is significantly associated with technological propensity.

IPM did not correlate, nor associate significantly with technological propensity or any of its underlying constructs (.000; p<.993). This finding may suggest that technological propensity is independent of climates or climate perceptions. Alternatively, this finding may suggest mean that that IPM-type work climates are not conducive to stimulating technological propensity.

Since IPM climates are associated with closed (Patterson, et al., 2005; Chesbrough, 2006),) and inward focusing (Patterson, et al., 2005) models, individuals operating in IPM-type climates may typically be unaware of the potential of new technologies and methodologies. They may also be unable to make use of any new technologies and methodologies in their research due to the restrictive, inward-focused and traditionally inclined nature of IPM-type climates (Patterson, et al. 2005).

6.3.2.4.2 Open Systems Model Climate is significantly associated with technological propensity

The Open Systems model (OSM) work climate also did not correlate or associate with technological propensity, or any of its underlying constructs (.016; p<.745). Upon closer inspection, however, outward focus (a sub-measurement of OSM climates) was found to correlate significantly with tolerance for disruption (p = .093) and collaborative propensity (p=.092). This indicates a relationship between open climates and technological propensity, amongst academic researchers. This finding may suggest that individuals that perceive their climate to be outward focused, (or, the extent to which work climates are adaptable and responsive to external influences) (West & Farr, 1990) will be more likely to collaborate more frequently. Such individuals may also be more adaptable to change (Patterson, et al., 2005). This holds important consequence for 6G theory, in that fostering climates that are outward focused and reflexive to external stimuli may be an important precursor to stimulating the adoption of new technologies and methodologies. This finding is also supported by the results of the qualitative analysis.

In summary, work climate perceptions are not directly associated with technological propensity, for the academic researcher sample. Upon closer inspection however, outward focus (a sub-component of OSM-type climates) is positively associated with some elements of technological propensity, although this effect size is relatively weak. A discussion pertaining to the mediating effect of personality on the relationship between technological propensity and productivity, now follows.

6.3.2.5 Hypothesis A5: Personality mediates the relationships between technological propensity and productivity

The results of the AR and CW analyses indicate that none of the factors of the FFM model of personality significantly mediate the relationship between technological propensity and productivity, in either the AR or CW samples. One potential interpretation of this finding is that in both the AR and CW contexts, adherence to tradition, standards and conventions may inhibit the uptake of new modes of productivity, regardless of differences in personality. In the academic context, this may be attributable to a routinisation of the academic research process (Anderson, et al., 2004), where paradigmatic conformity (Hanson, 1990; Campanario, 2009) may be favoured over exploration and adoption of new technologies and methodologies. In the CW context, adherence to standard procedure is rewarded; MTurk workers are paid for each HIT completed (Goodman, et al., 2013) and may therefore be expected to not seek out different ways of doing things. This however, may be unique to the case of MTurk. Lakhani and Panetta (2007) suggest that crowd-workers that contribute to open source software, such as Linux or to open source encyclopedias such as Wikipedia (Maehre, 2009), are often intrinsically motivated by enjoyment, creativity, stimulation and learning (Lakhani & Wolf, 2005).

Ins summary, none of the factors of the FFM Model of personality are significant mediators of the relationship between technological propensity and productivity. These findings are consistent across both the AR and CW samples. A discussion pertaining to the mediating effect of motivational values the relationship between technological propensity and productivity now follows.

6.3.2.6 Hypothesis A6: Motivational values mediate the relationship between technological propensity and productivity

The results of this analysis show that for both the AR and CW samples, self-transcendence, conservation and self-enhancement do not mediate the relationship between technological propensity and productivity. Like personality, this finding may be attributable to the effects of standardisation (Dewald, Thursby & Anderson, 1986), routinisation (Anderson, et al., 2004) and paradigmatic conformity (Campanrio, 2009; Bornman, et al., 2010), which may inhibit the adoption of certain new technological and methodological advancements to improve productivity. These findings suggest that this may be the case regardless of differences in

motivational values. Similarly, in the crowd-worker context, since MTurk workers are paid for the productivity (Goodman, et al., 2013), they may not experience a need to seek any different modes of productivity. There is however, one notable exception.

For the AR sample, openness to change does significantly mediate the relationship between technological propensity and productivity (.105; p<.000). Openness to change is also found to mediate this relationship in the crowd-worker sample, albeit negatively (-.026; p<.000). According to Schwartz (1992), openness to change is comprised of two underlying, lower-order motivational values: self-direction and stimulation. Self-direction relates to independent thought, creativity and exploration (Deci, 1976). Stimulation relates to excitement, novelty and challenge (Deci, 1976; Schwartz, 1992).

Since none of the other higher-order motivational values were found to significantly mediate this relationship, this finding suggests that only academic researchers who are open to change will experience a positive relationship between technological propensity and productivity. In other words, academic researchers who seek to seize opportunities offered by certain technological and methodological advancements may indeed produce more academic research output, only if they are open to change. This finding is significant in the greater context of this research, particularly the relationships surrounding 6G innovation and openness. It suggests that academic researchers who are motivated by excitement, novelty, stimulation and independent thought may be more likely to adopt 6G mechanisms and may produce more research output than their peers. This finding is supported by the qualitative analysis. It is also supported by literature. For Chesbrough (2003a; 2006), organisations that adopt open models of innovation may benefit from internal and external flows of knowledge, ideas and information. 6G innovation is premised on open innovation. Callaghan (2014a; 2016a) argues that some closed models of productivity have reached the limit of their natural S-Curves, and that that application of certain new open modes of productivity may enable scale advantages which could precipitate knowledge interactions and ultimately improve the probability of producing innovative output (Foster, 1986; Smith, 2010). Thus, if this argument is applied to the level of the individual, the adoption of some new, open modes of productivity may facilitate individual-level innovative performance. While the measure of productivity (journal articles published over time) may not necessarily be indicative of innovativeness (Rachal, et al., 2008), this finding shows that productivity may still improve. If individuals themselves are motivated

by openness to change, they may produce more output. In turn, such individuals may have a higher probability of producing breakthrough, radically innovative research output.

In the case of crowd-workers, it was found that openness to change also significantly mediates the relationship between technological propensity and productivity (-.026; p<.000). Since none of the higher order motivational values were found to significantly mediate this relationship, this finding suggests that only crowd-workers who are open to change will experience a negative relationship between technological propensity and productivity. In other words, crowd-workers who seek to seize opportunities offered by certain technological and methodological advancements will produce less output, if they are open to change. This may be attributable to the nature of MTurk work, where MTurk productivity may be a function of conscientious adherence to MTurk productivity norms. MTurk workers are only paid if they complete an HIT to the satisfaction of the requester (Kittur, 2010; Goodman, et al., 2013). Therefore, being open to experience, or being willing to complete HITs in a manner that piques creativity, excitement or independent thought (Schwartz, 1992) may be detrimental to MTurk productivity. Such individuals may therefore produce less output than their counterparts, who do adhere to the standards demanded of them by requesters. Again, it is stressed that this may not be the case on other crowd-work platforms such as InnoCentive or Wikipedia.

In summary, it is concluded that academic researchers who are open to change may experience a stronger relationship between technological propensity and productivity. Conversely, crowd-workers who are open to change may experience a weaker relationship between technological propensity and CWP. A discussion pertaining to the mediating effect of climate perceptions on the relationship between technological propensity and productivity now follows.

6.3.2.7 Hypothesis A7: Climate perceptions mediates the relationship between technological propensity and productivity

This hypothesis was tested for the AR sample only. According to the findings of this analysis, IPM does not significantly mediate the relationship between technological propensity and productivity (.002; p >.000). This finding is unexpected since theoretically, individuals with IPM-type climate perceptions would be expected to have low technological propensities, in comparison to their productivity (Patterson, et al., 2005; Callaghan, 2014a). OSM also did not significantly mediate the relationship between technological propensity and productivity

(-.003; p> .000). This finding is also unexpected since theoretically, individuals with OSM-type climate perceptions should have higher levels of both technological propensity and productivity (Patterson, et al., 2005; Callaghan, 2014a). A possible explanation for this finding is that climate perceptions alone are not sufficient to stimulate the adoption of new modes of productivity, nor productivity itself. Climate perceptions reflect perceived environments (Scott & Bruce, 1994), but this alone may not be sufficient to influence behaviour, motivations (Beer, Eisenstat & Spector, 1990), or productivity (Scott & Bruce, 1994).

In summary, work climate perceptions do not mediate the relationship between technological propensity and productivity. A discussion pertaining to the mediating effect of HCI on the relationship between technological propensity and productivity now follows.

6.3.2.8 Hypothesis A8: Human Capital Investments (HCI) mediates the relationship between technological propensity and productivity

For both the AR (-.043; p > .000) and CW (.021; p > .000) samples, HCI are not a significant mediator of the relationship between technological propensity and productivity. This suggests that experience and education do not impact the relationship between technological propensity and productivity. One possible explanation for this finding is that it is not simply HCI, but perhaps the diversity of HCI that may contribute to productivity. The findings of the qualitative study suggest that individuals with more diverse and varied sources of education, training and experience may be more open to the adoption of unconventional modes of production and may seek to explore outside the bounds of conventional wisdom. Black and Lynch (1996, p. 266) suggest that productivity or performance may ultimately be a function of the quality, rather than quantity of HCI; "It is not so much *whether* you train the workers, but rather, *what you train the workers in*, that affects… productivity."

In summary, these findings suggest HCI do not mediate the relationship between technological propensity and productivity. However, based on the findings of the qualitative study and supporting literature, it is possible that HCI diversity may mediate this relationship. This may present an interesting opportunity for further research on the potential effects of HCI diversity.

This concludes discussion of Research Question A. The results of quantitative analyses in relation to Research Question B, on the relationship between HCI and productivity, are now discussed.

6.3.3 Research Question B: What is the relationship between Human Capital Investments (HCI) and productivity?

To assess the relationship between human capital investments and productivity, the following hypotheses and sub-hypotheses were tested. The findings of the AR and CW analyses are discussed for each hypothesis and sub-hypothesis as follows.

6.3.2.1 Hypothesis B1: Human Capital Investments (HCI) are significantly associated with productivity

The results of the AR analysis indicate that HCI are indeed significantly and positively associated with productivity (.208; p<.000). This finding corroborates Becker's (1962) theory of human capital, which posits that the accumulation of education, training and experience are positively associated with productivity. For the CW sample however, HCI were found to not be significantly associated with CWP (.037; p<.415). This regression was conducted with inclusion of age as a regression covariate. Thus, this result suggests that the non-significant association between HCI and CWP may be over and above the influence of time alone. However, a post-hoc analysis (which excluded age as a covariate) produced the same result.

The result of both the AR and CW analyses tests indicates significant differences in the AR and CW contexts. In the case of academic researchers, it would be expected that the accumulation of experience would be positively associated with productivity. In the case of crowd-workers however, CWP is not dependent on education or experience. This finding supports Callaghan's (2014a) theory of 6G; that real-time productivity may indeed be possible by harnessing 6G mechanisms that offer economies of scale. For example, crowd-workers can produce large amounts of output in significantly less time without experience or knowledge (Kittur, 2010). It is acknowledged, however, that these measures of output are not comparable. It is necessary that academic researchers spend long periods of time producing journal articles (Gastel & Day, 2016), whereas crowd-workers need only a few minutes or hours to complete an HIT (Casler, Bickel & Hackett, 2013; Goodman, et al., 2013). Notwithstanding, these

findings do show that 6G mechanisms (such as MTurk) may provide a conduit through which some forms of real-time productivity may be enabled. It remains to be seen if the application of 6G to the process of academic research could produce similar results. To further investigate this relationship, the mediating effects of personality, motivational values and work climate perceptions on the relationship between HCI and productivity were tested. The results of those analyses for both the AR and CW samples, are now discussed as follows.

6.3.2.2 Hypothesis B2: Personality mediates the relationship between HCI and productivity

In both the AR and CW analyses, none of the underlying personality traits of the Five Factor Model were found to significantly mediate the relationship between HCI and productivity (or CWP). Black and Lynch (1996) suggest that it is the variety and diversity of HCI (rather than the accumulation of HCI) that predicts work performance (or productivity). The findings of the qualitative analysis also suggest that HCI diversity may be a more suitable predictor of performance and productivity than the accumulation of HCI, in the academic research context. The measurement of HCI used in this study does not reflect HCI diversity, only total accumulated years education and experience. Thus, one potential interpretation of this finding is that the accumulation of HCI may not be related to productivity. Instead, productivity may be a function of the diversity and variety of accumulated education, experience and training (Black & Lynch, 1996). Therefore, differences in personality would not have any significant impact on the relationship between HCI and productivity. However, differences in personality may indeed impact the relationship between HCI diversity and productivity. This represents another opportunity for further research.

In summary, this suggests that this relationship will remain unchanged regardless of differences in personality, both in the case of academic researchers and crowd-workers. A discussion of the mediating effect of motivational values on the relationship between HCI and productivity, now follows.

6.3.2.3 Hypothesis B2: Motivational values significantly mediate the relationship between HCI and productivity

Like personality, none of Schwartz' (1992) higher order values of motivation significantly mediate the relationship between HCI and productivity, for either the AR or CW samples. Again, this finding may be attributable to the measurement of HCI used in this research, which does not take HCI variety and diversity into account. Thus, like personality, it may be possible that motivational values would impact the relationship between HCI diversity and productivity. However, motivational values do not mediate the relationship between the accumulation of education, experience and training, measured in years and productivity. In summary, the relationship between HCI and productivity remains unchanged by differences in motivational values, both in the cases of academic researchers and crowd-workers. A discussion on the mediating effect of work climate perceptions on the relationship between HCI and productivity now follows.

6.3.2.4 Hypothesis B4: Work climate perception mediates the relationship between HCI and productivity

As previously discussed, the CW sample was not tested for work climate perceptions, since most MTurk workers tend to work from home (Goodman, et al., 2013). Neither IPM, nor OSM significantly mediate the relationship between HCI and productivity. Like personality and motivation, these findings indicate that work climate perceptions do not significantly mediate the relationship between HCI and productivity. Like previous tests of mediation, this finding may also be attributable to the measurement of HCI used in this research, which measured only the accumulated numbers of years of education and experience. However, as previously noted, it may also be possible that climate perceptions are not significant individual-level predictors of performance (Scott & Bruce, 1994). According to the result of the qualitative analysis, climate perceptions may be external drivers of performance, rather than internal. It may be possible therefore, that climate perceptions alone are not strong enough predictors of performance.

This concludes discussion of Research B. The findings related to Research Question C, on the interactive effects of gender, field of study and profession are now reviewed.

6.3.3 Research Question C: The interactive effects of gender, field of study and profession

The moderating effects of gender and field of study on the relationships between technological propensity, productivity and HCI was investigated. In both the AR (.217; p<.727) and CW (.025; p<.298) analyses, it was found that gender does not significantly moderate the relationship between technological propensity and productivity. The results of the CW analysis indicate that gender does not moderate the relationship between HCI and CWP (.325; p<.478). However, the results of the AR analysis suggest that gender does indeed moderate the relationship between HCI and productivity (.086; p<.001). According to this finding, men have a slightly stronger relationship between HCI and productivity than women. Those men with more years of experience (HCI) will inadvertently have produced greater quantities of research output, than their women counterparts. This finding is most likely attributable to the effects of family life spillovers. Leahey (2006) suggests that women tend to be slightly less research productive than men, owing to duties associated with maternity leave and raising children. Furthermore, women may in some cases specialise less than men, which may be another contributing factor to lower levels of research output in females (Leahy, 2006). As responsibilities associated with family life increase over time, research productivity may therefore decrease, while these effects may not impact men as strongly.

Field of study was found not to significantly moderate the relationship between technological propensity and productivity. This finding is in contrast to the findings of the qualitative study, which suggest that individuals associated with fields in biology, microbiology, health and medicine may have higher levels of technological propensity and may in some cases therefore also produce more research output. Field of study also did not significantly moderate the relationship between HCI and productivity. Again, this finding is in contrast to those of the qualitative study. These findings also conflict with the assertions of Gonazelz-Brambila and Veloso (2007), who suggest that academic researchers in biological, health and medical fields may produce more research output than those in the humanities. Gonzalez-Brambila and Veloso (2007) also suggest that academic researchers in STEM-related fields (referred to as the ‘exact’ sciences) may produce more output as a function of their experience and education, than other academic researchers. It seems however that these differences may not be significant in the context of this research.

Crowd-workers that work in STEM-related professions might be expected to have higher levels of technological propensity than their counterparts, since STEM-related careers are often associated with the use, or adoption of new and emerging technologies (Bowers, 2017). However, the results of the crowd-worker analysis indicate that profession does not significantly moderate the relationship between technological propensity and productivity (.609; p<.909). Profession also does not significantly moderate the relationship between HCI and productivity (-.186; p<.949). This finding suggests that professional differences may become void in the 6G space. In conjunction with previous findings, which suggest that gender also does not moderate these relationships in the 6G space, this argument is extended to suggest that numerous other individual differences may become void in the 6G space. Indeed, examination of moderation plots (see Chapter 5), seem to suggest very small and non-significant differences amongst men and women crowd-workers, and STEM and non-STEM crowd-workers. In contrast, although mostly not significant, examination of moderation plots (Chapter 5) seem to suggest that there may be greater differences in the relationships between technological propensity, HCI and productivity, amongst academic researchers. It may therefore be possible that in 6G space, individual-level productivity may become homogenous across gender and professional boundaries.

One possible explanation for this finding is that crowd-work may imitate naturally-occurring, complex, biological systems, such as swarms of bees. In these types of systems, performance is a reliant on overall trends of entire populations, rather than individuals or small groups. Adam Smith's 'Invisible Hand' hypothesis purports that an unknown force (or, 'invisible hand') directs knowledge interactions, in decentralised systems (Kochugivondan & Vriend, 1998). This may be attributed to aggregate crowd effects, or the 'wisdom' of crowds, as described by Surowiecki (2004). It is not the skills, knowledge and ability of a single crowd-worker that determines innovative output, but rather the combined, decentralised problem-solving capability of the entire collective, which in turn, depends on the diversity of the crowd. For Surowiecki (2004, p. xv11):

> If you put together a big enough and diverse enough group of people and ask them to make decisions affecting matters of general interest, that group's decisions will, over time, be intellectually [superior] to the isolated individual, no matter how smart or well-informed he is.

In the qualitative analysis however, attention was drawn to the notion of the *diversity* of HCI. Individuals who have more diverse educations, who come from more diverse backgrounds, or who have more varied training, experience and education, are more likely to adopt unconventional modes of productivity and are highly likely to produce research breakthroughs.

In summary, at the level of the individual, diverse HCI inputs contribute to innovative performance. For Smith (2010), the interaction of diverse knowledge inputs stimulates innovation. For Surowiecki (2004), the innovative potential of crowds is determined by their diversity. However, according to the findings of this study, individual differences such as gender and profession may be become mitigated, at the crowd-level. This is contradictory. A possible explanation for this contradiction, is that even though some individual differences may be mitigated at the aggregate level of the crowd, specialised and diversified skills and abilities of individual crowd-members, are still imperative to the production of innovation. Therefore, diversity may not be a function of biographical characteristics, such as gender, profession or nationality, but rather a function of the diversity of one's education, training and experience. Black and Lynch (2001), comment on the relationship between HCI and productivity: "it is not so much *whether* you train the workers, but rather, *what you train the workers in,* that affects productivity". Similarly, it is not whether a diverse crowd exists, but whether the composition of the crowd's collective HCI is sufficiently diverse, that affects productivity. Therefore, in the 6G space, diversity refers to individualised skills and abilities which are developed by education, training and experience, rather than generic biographical differences. In naturally occurring, decentralised, large collectives, such as swarms of bees, each bee is assigned a specialised skill or task that only they can perform. Similarly, in crowds, individual crowd-members with unique skills or abilities complete tasks that are uniquely assigned to them, until the problem space is eroded. The productivity of the crowd is not dependent on the individual but is dependent on the collective. Conversely, the breakthrough, radically innovative potential of the crowd is not based on the diversity of the collective, but the diversity of individuals. This represents an interesting opportunity for further study, regarding the effects of differences in nationality, language and geographical location, amongst other potential differentiators. The results of the quantitative analyses are summarised in Table 63, below

Table 63: Summary of results of quantitative analyses

Research Question A: What is the relationship between technological propensity and productivity?			
Hypothesis	**Sample**	**Significant regression results**	**Significant correlations**
Hypothesis A1: Technological propensity is associated with productivity			
	AR	- Technological propensity is not associated with productivity	- Collaborative propensity is positively correlated with productivity - Crowd propensity is negatively correlated with productivity
	CW	- Technological propensity is not associated with productivity	- Collaborative propensity is negatively correlated with productivity
Hypothesis A2: Personality is associated with technological propensity			
	AR	- Openness to experience is positively associated with technological propensity - Neuroticism is negatively associated with technological propensity	- Openness to experience is positively correlated with technological propensity
	CW	- Openness to experience is positively associated with technological propensity - Extraversion is positively associated with technological propensity - Conscientiousness is positively associated with technological propensity - Agreeableness is positively associated with technological propensity	- Openness to experience is positively correlated with technological propensity - Extraversion is positively correlated with technological propensity - Agreeableness is positively correlated with technological propensity - Neuroticism is negatively correlated with technological propensity

			- Neuroticism is negatively associated with technological propensity	
	Hypothesis A3: Motivation is associated with technological propensity			
		AR	- Self-transcendence is positively associated with technological propensity - Openness to change is positively associated with technological propensity - Conservation is negatively associated with technological propensity	- Self-transcendence is positively correlated with technological propensity - Conservation is positively correlated with technological propensity - Openness to change is positively correlated with technological propensity
		CW	- Self-transcendence is positively associated with technological propensity - Self-enhancement is positively associated with technological propensity - Conservation is positively associated with technological propensity - Openness to change is positively associated with technological propensity	- Self-transcendence is positively correlated with technological propensity - Self-enhancement is positively correlated with technological propensity - Conservation is positively correlated with technological propensity - Openness to change is positively correlated with technological propensity
	Hypothesis A4: Work climate is associated with technological propensity			
		AR	- Work climate is not associated with technological propensity	- Work climate is not correlated with technological propensity
	Hypothesis A5: Personality mediates the relationship between technological propensity and productivity			

		AR	- Personality does not mediate the relationship between technological propensity and productivity	
		CW	- Personality does not mediate the relationship between technological propensity and productivity	
	Hypothesis A6: Motivation mediates the relationship between technological propensity and productivity			
		AR	- Openness to change positively mediates the relationship between technological propensity and productivity	
		CW	- Openness to change negatively mediates the relationship between technological propensity and productivity	
	Hypothesis A7: Work climate mediates the relationship between technological propensity and productivity			
		AR	- Work climate does not mediate the relationship between technological propensity and productivity	
Research Question B: What is the relationship between HCI and productivity?				
	Hypothesis B1: HCI is associated with productivity			
		AR	- HCI are associated with productivity	- HCI are correlated with productivity
		CW	- HCI are not associated with productivity	- HCI are not correlated with productivity
	Hypothesis B2: Personality mediates the relationship between HCI and productivity			
		AR sample	- Personality does not mediate the relationship between HCI and productivity	
		CW	- Personality does not mediate the relationship between HCI and productivity	
	Hypothesis B3: Motivation mediates the relationship between HCI and productivity			
		AR	- Motivation does not mediate the relationship between HCI and productivity	

		CW	- Motivation does not mediate the relationship between HCI and productivity	
	Hypothesis B4: Work climate mediates the relationship between HCI and productivity			
		AR	- Work climate does not mediate the relationship between HCI and productivity	
Research Question C: What are the interactive effects of gender and field of study/profession on the relationships between technological propensity, HCI and productivity?				
	Hypothesis C1: Gender moderates the relationship between technological propensity and productivity			
		AR	- Gender does not moderate the relationship between technological propensity and productivity	
		CW	- Gender does not moderate the relationship between technological propensity and productivity	
	Hypothesis C2: Field of study/profession moderates the relationship between technological propensity and productivity			
		AR	- Field of study does not moderate the relationship between technological propensity and productivity	
		CW	- Profession does not moderate the relationship between technological propensity and productivity	
	Hypothesis C3: Gender moderates the relationship between HCI and productivity			
		AR	- Gender does moderate the relationship between HCI and productivity	
		CW	- Gender does not moderate the relationship between HCI and productivity	
	Hypothesis C4: Field of study/profession moderates the relationship between HCI and productivity			
		AR sample	- Field of study does not moderate the relationship between HCI and productivity	

		CW	- Profession does not moderate the relationship between HCI and productivity	

Having concluded discussion of the qualitative and quantitative findings, the results of both of these analyses is now discussed, along with literature, in a synthesis of qualitative and quantitative findings.

6.4 SYNTHESIS OF QUALITATIVE AND QUANTITATIVE FINDINGS

The focus of this research is on the relationships surrounding technological propensity and productivity. In the context of this research, technological propensity is defined as the extent to which individuals seize opportunities offered by new technological and methodological advancements, such as crowdsourcing and crowdfunding, to improve performance, or productivity. According to Callaghan (2014a; 2015a), crowdsourcing and crowdfunding may offer significant scale advantages, when applied to the research process. Crowdsourcing may offer high volume data collection (Good & Su, 2013), and may also offer analysis advantages (Kashima, Oyama, & Baba, 2017). Crowdfunding may offer scalable funding opportunities, where diverse sources of funds can be obtained across organisational, geographical or political boundaries, rather than traditional single-funder sources (Rubinton, 2011). Taking advantage of these opportunities therefore may offer an increased probability of producing radical 'breakthrough' innovations, which may help to rapidly generate solutions to pressing social problems.

The focus of this research is an investigation of the relationship between technological propensity and productivity. In other words, this research seeks to investigate if the proclivity to harness scale opportunities offered by certain new technologies and methodologies is positively associated with research output over time.

This relationship was investigated from three different perspectives. Firstly, data collected from a sample of highly innovative, award-winning scientists was analysed qualitatively. Data collected from this sample provides insight into the relationship between technological propensity and 'breakthrough' research productivity (BRP). Secondly, data collected from a sample of South African academic researchers was analysed quantitatively. This data provides insight into the relationship between technological propensity and academic researcher productivity (referred to here as 'productivity'). Thirdly, and finally, data collected from a sample of 'crowd-workers' (or, users of Amazon's online crowdsourcing Mechanical Turk platform) was analysed quantitatively. This data provides insight into the relationship between

technological propensity and crowd-work productivity (CWP). The objectives of the qualitative analysis were i) to determine the drivers of BRP and ii) to determine the extent to which new technologies and methodologies such as crowdsourcing and crowdfunding may contribute to BRP. The objectives of the subsequent quantitative analyses were to investigate the relationships surrounding technological propensity and productivity in different contexts; firstly, in the context of academic research, and secondly in the context of the 6G space. In the context of this research, the '6G space' is defined as the context within which crowdsourcing, or crowdfunding is already in use (i.e. on Amazon's Mechanical Turk platform, which is a crowdsourcing website).

The relationship between individual-level innovation and productivity has been investigated extensively (West & Farr, 1990; West, 2002; Link, Siegel & Bozeman, 2007; Bozeman, Fay & Slade, 2013). King and Anderson (2002) put forth a comprehensive typology of innovative performance facilitators, which includes personality, motivation, job characteristics and cognitive ability. However, this model does not consider new technologies and methodologies such as crowdsourcing or crowdfunding (collectively called '6G'). For this reason, this research is based on a modified version of King and Anderson's (2002) typology, which includes technological propensity as a potential additional facilitator of performance, or productivity.

Qualitative analysis revealed that BRP is driven by a combination of internal and external factors. According to the results of the qualitative analysis, internal drivers include personality, motivation and innate ability. External drivers include work climate, human capital investments (HCI) and resource availability. It was also found that technological propensity may, to some extent, be an internal driver of BRP. A model of drivers of BRP was derived from qualitative findings.

The associations between internal and external factors, and productivity were thereafter investigated quantitatively. First, these associations were tested for a sample of South African academic researchers. This analysis was conducted to investigate the relationships surrounding technological propensity and productivity in the academic research space. Second, these associations were tested for a sample of MTurk crowd-workers. This analysis was conducted to investigate the relationships surrounding technological propensity and productivity in the

6G space. The association between the literature, the qualitative and quantitative analyses is depicted in Figure 35, below:

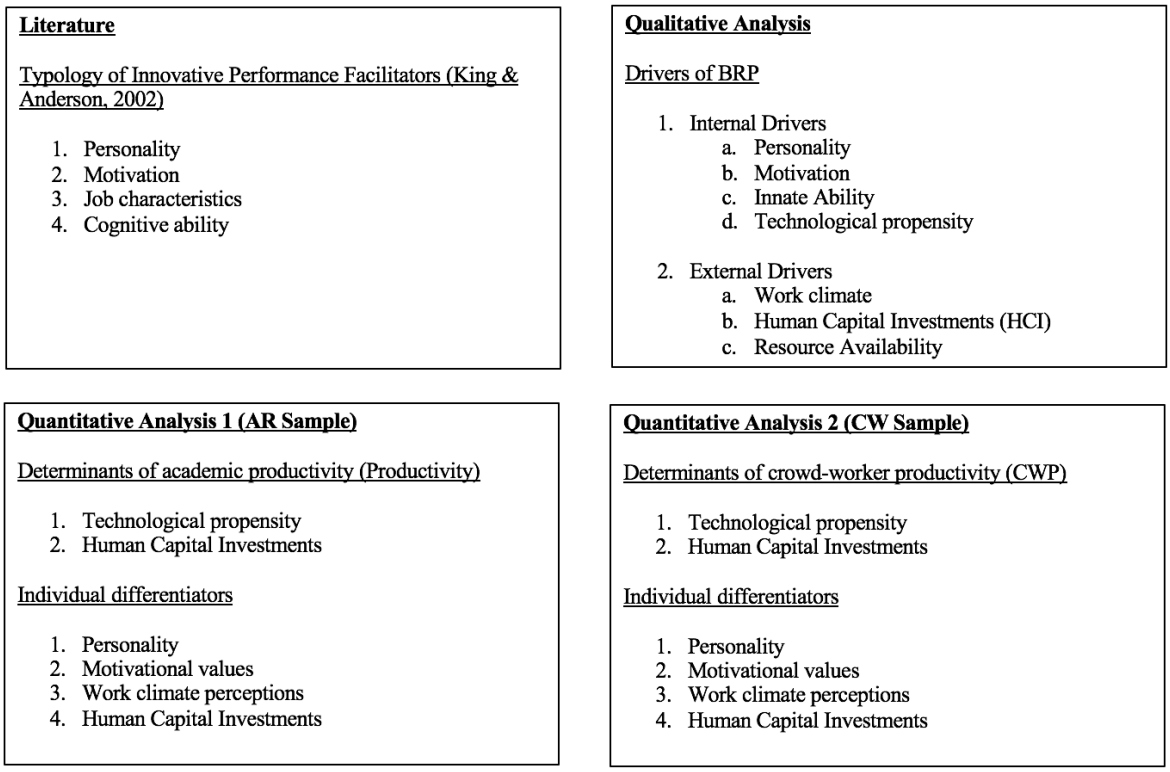


Figure 35: Relationship between literature, qualitative and quantitative analyses

Following the structure of Figure 33, a synthesis of literature, qualitative and quantitative results is now provided. Qualitative and quantitative findings are compared and contrasted to the literature to arrive at a holistic synthesis.

During qualitative analysis, a process of proposition derivation was undertaken. Propositions were derived from qualitative data. During quantitative analysis, a process of hypothesis testing was undertaken. Hypotheses were derived from the literature. Each of the qualitative propositions and sub-propositions are now discussed, in relation to the findings of the quantitative hypothesis and sub-hypothesis testing. First, the measurement and relationships surrounding the dependent variable, for each of the three samples, is discussed. A discussion pertaining to the relation between proposition derivation and hypothesis testing follows.

6.4.1 The Dependent Variable: Productivity

For the purposes of this research, three different types of productivity were investigated. These include i) 'breakthrough' research productivity (BRP), ii) academic research productivity and iii) crowd-worker productivity. Respondents in the qualitative sample are assumed to have achieved a high level of 'breakthrough' research productivity. Notable scientific awards (such as the Nobel Prize) are awarded to individuals who have made "academic, cultural or scientific advances," (Cao, 2004, p. 153). In other words, such individuals have 'broken through' convention, in the form of a radical innovation. As a result, such individuals have attained high status and have received recognition and reward.

For respondents in the quantitative AR sample, productivity was measured by total number of journal publications, over a number of the years of experience as an academic researcher. This ratio of journal articles over time is commonly used as a measure of productivity (Rachal, et al., 2008). However, although academic researchers have a social obligation to produce social innovations (Radder, 2010), the extent to which their productivity is innovative, is unknown. For this reason, this measure of productivity is simply referred to as 'productivity'. For respondents in the CW sample, 'crowd-worker productivity' (CWP) was measured by a total number of completed MTurk HITs over a total number of years of experience as an MTurk worker. This ratio of productivity is also not indicative of innovativeness. However, MTurk workers are not assumed to have a social responsibility to innovate. Given average productivity scores, it was found that crowd-workers produce significantly more output than academic researchers. This is most likely due to the nature of crowd-work, which occurs in real-time and is not as an extensive undertaking as the publication of a journal article. Furthermore, academic researchers tend to have other job responsibilities, such as teaching and administrative duties (Leahey, 2006; Bozeman & Gaughan, 2011). It was also found that respondents in the AR sample supported, on average, more dependent children in their families than the crowd-worker sample, which may further impact productivity.

It is stressed that the comparison of outcomes is not the objective of this assessment. Rather, the objective is the comparison of the relationship between technological propensity and productivity, across a productivity spectrum. The findings of the qualitative analysis provide indication that there exist certain internal and external drivers of breakthrough research productivity which may be useful, applied in the academic research context. Furthermore, the

findings of these quantitative analyses suggest that if some of the qualities of crowd-work productivity were to be harnessed and transposed to the academic research context, it may be possible to enhance the rate at which academic research productivity occurs. This, in turn may potentially accelerate the rate at which radical breakthrough innovations are generated. To further synthesise the qualitative and quantitative findings of this research, each of the derived propositions and results of hypothesis testing are now discussed, in relation to literature. Proposition A, related to the internal drivers of BRP, is discussed first.

6.4.2 Internal drivers of productivity

According to the results of the qualitative analysis, internal drivers of BRP include personality, motivation, innate ability and technological propensity. These relationships form the basis for the derivation of Proposition A: internal drivers are related to BRP. From this main proposition, sub-propositions were derived, each of which relates to a different internal driver. Since the primary focus of this research is on the relationship between technological propensity and productivity, this relationship is discussed first.

6.4.2.1 Technological Propensity and Productivity

As previously discussed, technological propensity is a measurement of the extent to which individuals seize new technological and methodological opportunities that offer significant economies of scale, such as crowdsourcing and crowdfunding. Qualitative analysis revealed that technological propensity may be a driver of BRP. The results of the qualitative analysis discovered several interlinking themes related to technological propensity. These include i) open orientation, ii) crowdsourcing, iii) crowdfunding, iv) technology use, v) management/acceleration and vi) journal publication perception. A similar technological propensity measure was derived from the literature. This technological propensity scale comprises of open orientation, tolerance for disruption, technology use, crowd propensity and collaborative propensity.

Amongst qualitative respondents, terms such as ‘crowdsourcing’ and crowdfunding’ are generally considered contrived and not applicable to scientific or academic research. Similarly, some qualitative respondents argued that scientific research cannot be accelerated. This finding may be attributable to the advanced mean age (73.5 years) of the qualitative sample. Barrick,

et al. (1998) suggest that there may that be a negative relationship between age and adoption of new technology. Costa and McCrae (1990), note that individuals with lower levels of openness to experience tend to follow conventional ways of thinking, and may be more risk averse than others. According to Specht, et al. (2011), openness tends decrease in old age. Many respondents admitted their disinterest in new technologies, although many did signify their understanding of its importance. Conversely, much of the qualitative sample described the importance of an open orientation, or a general openness to new ideas, techniques and methods. Some noted that the production of breakthroughs requires adaptation to changing methods and technologies. Collaboration was cited as the key driver of BRP. Individuals who collaborate across institutions and disciplines are more likely to produce breakthroughs. This finding is strongly supported by innovation management literature (Smith, 2010). The role of management was also described. According to the qualitative findings, ideal scientific management should provide a high degree of freedom and flexibility, cultivate an open work climate and foster collaboration.

In the qualitative analysis, journal publication perception was used to assess technological propensity. In general, respondents fell into two categories, related to journal publication perception. These included 'pro-publication' and 'anti-publication'. Pro-publication respondents tend to believe that journal publications must maintain high and rigid levels of quality control. Furthermore, journal publications should focus on publishing incremental innovations, rather than radical innovations. For anti-publication respondents, journal publications may represent an outmoded form of research publication since they are overly rigid and inflexible. For these respondents, online journals and conferences are better suited to modern research publication.

A primary tension uncovered during qualitative analysis is that of openness versus conventionality. For many qualitative respondents, conformity to orthodoxy and traditionalism is imperative in the pursuit of scientific discovery. However, at the same time, openness, flexibility and 'big picture' thinking is required to attain radical breakthroughs. This tension underpins the findings of the qualitative analysis. For this reason, technological propensity may be, in some cases, associated with BRP. However, the influence of age, conformity and HCI may confound this relationship. This finding relates to the notion of 'innovation gatekeepers' (Anderson, et al., 1998; Anderson, Potocnik & Zhou, 2014). As previously discussed, most of the qualitative sample were of an advanced age and well-experienced. Despite their notable

achievements of breakthrough research productivity, these respondents may have experienced prolonged exposure to systems that are inherently non-innovative, inflexible and tied to conventional wisdom. The journal publication is one example of this. This, in turn, may inhibit technological propensity, which may be considered contrary to traditional methods of scientific and academic research.

In the quantitative analyses, tests of regression were conducted to investigate the relationship between technological propensity and productivity. It was found that technological propensity is not significantly associated with productivity, in both the AR and CW samples. However, according to the results of the tests of correlation, some forms of technological propensity may be correlated with productivity. In the AR sample, collaborative propensity was found to be significantly positively correlated with productivity. However, in the 6G space, a significant negative correlation suggests that crowd-workers are more productive when they are less collaborative. This suggests that collaboration is not necessarily a driver of productivity, in the 6G space. According to Surowiecki (2004), crowds tend to perform better when individual members are not concerned with the entire problem, but only the component of the problem that requires their attention. This is unlike the academic space, which requires full knowledge of the problem at hand, and which therefore makes collaboration useful. This finding is in line with the findings of previous studies that investigate publication productivity (Sooryamoorthy & Shrum, 2007; Ynalvez & Shrum 2011).

In the AR analysis, it was discovered that individuals with high levels of crowd propensity (or, the extent to which individuals are likely to employ crowdsourcing and crowdfunding for their research) are *less* research productive. This suggests that individuals who are not interested in adopting crowdsourcing or crowdfunding, and who therefore tend to adhere to traditional methods of research, are more productive than their counterparts. A possible explanation for this is that academic research productivity tends to increase over time (Costas & Bordons, 2011). However, openness, as a personality trait, tends to decrease, as one ages (Egloff & Schmukle, 2011). It is likely that older AR respondents are less interested in new technologies and methodologies than their younger counterparts (Barrick, et al., 1998; Specht, et al., 2011). This is also supported by the results of the qualitative analysis. This finding is also related to the theory of academic research routinisation. It is possible that prolonged exposure to systems that are non-innovative may decrease an individual's proclivity to be open (Anderson, 1998; Anderson, Potocnik & Zhou, 2014). In other words, the more time an individual has spent as

an academic researcher, the less interested they may become in new technologies and methodologies.

Further quantitative analyses were conducted to assess the relationships between personality, motivational values, work climate perceptions, HCI and technological propensity. Personality was tested for association with technological propensity. For the AR sample, it was found that conscientiousness, agreeableness and extraversion are not associated with technological propensity. However, openness to experience is positively associated with technological propensity. Neuroticism is negatively associated with technological propensity. Academic researchers who are more open to experience and less neurotic are more likely to adopt new technologies and methodologies such as crowdsourcing and crowdfunding. For the CW sample, openness to experience, extraversion, conscientiousness and agreeableness were all positively associated with technological propensity. Again, neuroticism was found to be negatively associated with technological propensity. These findings indicate that neurotic individuals are not likely to adopt new technologies and methodologies to improve their productivity, in either context. However, individuals that are open to experience, or those who are artistic, curious, imaginative and insightful (McCrae & John, 1992; Mueller, Melwani & Goncalo, 2012), are likely to have higher technological propensities.

Motivational values were also tested for association with technological propensity. For the AR sample, it was found that self-transcendence and openness to change are positively associated with technological propensity. Conservation is negatively associated with technological propensity. According to Callaghan (2014a), crowdsourcing and crowdfunding offer significant opportunities to solve pressing social problems, such as the spread of disease. Viral infections are extremely efficient because they spread exponentially and probabilistically. Combatting these, therefore, requires an equivalently efficient response. Crowdsourcing and crowdfunding also function exponentially and probabilistically and may therefore represent a suitable counter-measure to the spread of disease. This social imperative is one of the key principles of 6G theory (Callaghan, 2014a; 2015a). The application of new methodologies such as crowdsourcing and crowdfunding to the research process potentially offer significant economies of scale in data collection and analysis (Afuah & Tucci, 2012; Torr-Brown, 2013). Further, the application of these methodologies to the research process may also offer synergies with Big Data and Big Data Analytics (Taylor, et al., 2014; Rosenberg, 2016), which have become increasingly complex (Reichman, et al., 2011). Ofli, et al. (2016) suggest that the

integration of Big Data Analytics and crowdsourcing may offer radical advancements in disaster response. Costa (2014) suggests the same, in biomedicine. For Rosenberg (2016), the combination of artificial intelligence systems and large collectives of people (crowds) might lead to the development of a networked super-intelligence that combines human interests, values and morals. The use of crowdsourcing and crowdfunding may offer significant economies of scale in both data collection and analysis

It is expected therefore, that individuals that would adopt crowdsourcing and crowdfunding, would also be motivated by humanistic and universal motivational forces (i.e. self-transcendence). For Schwartz (1992), openness to change is comprised of self-direction and stimulation. Individuals that are open to change are motivated by independent thought, exploration, creativity, novelty and overcoming challenges. Such individuals are also more likely to adopt new technologies and methodologies such as crowdsourcing and crowdfunding, since these may represent exciting, novel developments that offer opportunities unlike their traditional counterparts. The negative association between conservation and technological propensity is also expected. Individuals that are conservative, traditional and who look to conformity and security are not expected to adopt new and unknown methodologies.

For the CW sample, self-transcendence, self-enhancement, conservation and openness to change were all found to be positively associated with technological propensity. Like academic researchers, self-enhancement and openness to change would be expected to be associated with technological propensity. Conservation however, would be expected to be negatively associated with technological propensity, as is the case for the AR sample. However, it is possible that for crowd-workers, crowdsourcing and crowdfunding already represent traditional means of productivity, and therefore offer security and conformity. This is unlike the case of academic researchers, to whom crowdsourcing and crowdfunding represent the unknown. Self-enhancement was also found to be positively associated with technological propensity for crowd-workers. According to Schwartz (1992), self-enhancement relates to individuals who are motivated by achievement and power. Again, this indicates that for crowd-workers, crowdsourcing and crowdfunding represent a well-established, useful and traditional means of improving productivity. If harnessed efficiently, these may result in high levels of performance and productivity, essentially driving achievement and power-related motivations.

Work climate perceptions were found to be not directly associated with technological propensity. However, outward focus (a sub-component of OSM-type climates) is positively correlated with some elements of technological propensity. This suggests that outward focusing work climate perceptions may be conducive to technological propensity.

Tests of mediation were conducted to further investigate the relationship between technological propensity and productivity. For both AR and CW samples, personality, HCI and work climate perceptions do not mediate the relationship between technological propensity and productivity. However, for the AR sample, openness to change, as a higher-order motivational value, does positively mediate this relationship. Conversely, in the CW sample, openness to change negatively mediates this relationship. This finding may reflect differences between the academic and non-academic contexts. According to Schwartz (1992), openness to change comprises of lower order values such as stimulation and self-direction. Self-direction relates to motivations that seek independent thought and exploration. Stimulation relates to motivations that seek excitement and novelty. In the academic context, technological propensity may represent a means to satisfy stimulation and self-direction motivations, because the adoption of new technologies or methodologies may represent a new, unconventional mode of productivity. Conversely, in the crowd-work context, the adoption of crowdsourcing or crowdfunding is an already accepted, conventional mode of productivity, and may therefore not fulfill self-direction or stimulation motivations.

According to the results of the qualitative analysis, other internal drivers of BRP include personality, motivation and innate ability. The relationship between personality and productivity is discussed next, as follows.

6.4.2.2 Personality and Productivity

The findings of the qualitative analysis revealed that personality is related to BRP. According to this analysis, the personality traits that are conducive to BRP include: i) openness, ii) conscientiousness, iii) enthusiasm, iv) extraversion and v) humility. This model of personality, derived from qualitative analysis is similar to that of the Big Five Model, which comprises of openness to experience, extraversion, conscientiousness, neuroticism and agreeableness (Costa & McCrae, 1990). The notable difference between these models, however is the substitution of agreeableness and neuroticism with humility and enthusiasm. This is expected, since it

would be unlikely that neuroticism and agreeableness would drive BRP. In this sense, enthusiasm may represent a form of extraversion (McCrae & John, 1992; Grant, 2013). Extraverted individuals are often perceived as enthusiastic, outgoing, energetic and talkative (Costa & McCrae, 1992; Grant, 2013). Humility may be, to some, extent, a similar version of neuroticism or agreeableness. Following McCrae and John (1992), agreeable individuals tend to be appreciative, trusting modest and compassionate; traits which could be perceived as humble. Similarly, neurotic individuals tend to be anxious, and self-conscious; traits that could be perceived to be humility. Notwithstanding these similarities, these findings suggest that neuroticism and agreeableness, as per their definitions as parts of the Big Five model, are not conducive to BRP. The incidence of neuroticism, in particular, may act as an impediment to productivity, since qualitative respondents frequently cited the importance of emotional stability, perseverance and persistence, traits that do not fit the description of neuroticism (Costa & McCrae, 1992; McCrae & John, 1992; Grant, 2013). If the respondents in the qualitative sample are taken to represent the high end of breakthrough, radically innovative productivity (evidenced by their breakthrough achievements), then these findings may offer useful applications for academic researchers, who seek to improve breakthrough research productivity. Thus, an implication that derives from this finding is that academic researchers who seek to improve the breakthrough, radically innovative potential of their research output should strive to be open, conscientious, enthusiastic, extraverted and humble. Conversely, such academic researchers should also strive to not be neurotic or agreeable.

In the quantitative analysis, crowd workers had significantly higher mean levels of agreeableness, conscientiousness and openness to experience, than academic researchers. Costa and McCrae (1990) note that individuals with lower levels of openness to experience tend to follow conventional ways of thinking and in some cases, may also be more risk averse than others (Barrick et al., 1998; Carney, Cuddy & Yap, 2010). This may in turn link to higher levels of conscientiousness. This finding suggests that crowd-workers are significantly more agreeable and conscientious than academic researchers, but also slightly more open to experience. A test of mediation revealed that none of the factors of the FFM Model of personality are significant mediators of the relationship between technological propensity and productivity, across both the AR and CW samples. The relationship between motivation and productivity is discussed next.

6.4.2.3 Motivation and Productivity

Qualitative analysis revealed that motivational values that are conducive to BRP include i) intrinsic motivation, ii) satisfaction, iii) resilience, iv) worldview and v) extrinsic motivation. This finding represents a combination of Schwartz' (1992) model of higher order motivational values and Ryan and Deci's (2000) model of the Self-Determination Theory (SDT) continuum. According to the qualitative findings, the pursuit of BRP relies on a combination of different motivational forces, which lie across the SDT continuum and range from intrinsic to extrinsic. Between pure intrinsic and extrinsic motivational forces, however, lies a modified form of Schwartz's (1992) model of higher order motivational values, which, according to Schwartz (1992) is comprised of self-transcendence, self-enhancement, openness to change and conservation. 'Worldview' is seen as synonymous with self-transcendence, while 'satisfaction' may be a form of self-enhancement. Resilience may be a form of conservation since both relate to staples of conformity and tradition. Openness to change however, does not seem to be represented in the qualitative findings. It may be possible that openness to change is represented by intrinsic motivation, since for Schwartz (1992), openness to change is made up of lower order values such as self-direction and stimulation, which are both intrinsic forces. Furthermore, extrinsic motivation may form a component of self-enhancement, which is made up of lower order values such as achievement and power. Again, these findings offer useful insights, which may be applied at the level of academic researchers who seek to attain a higher breakthrough level of research output. Shifting across the SDT scale towards more intrinsic motivations may enhance BRP. This suggests that researchers who pursue research goals that are proximal to their own internal motivations, or those that pique curiosity may thus stimulate creativity and therefore may be more likely to be radically innovative.

Like personality, differences between AR and CW samples were minimal. Academic researchers had slightly lower average levels of conservation and self-enhancement than crowd-workers. However, crowd-workers had, on average, slightly lower levels of self-transcendence and openness to change than academic researchers. This finding may be attributable to the selection process of academic education, which selects for certain characteristics (Link, Sigel & Bozeman, 2007). However, these findings do show relatively similar motivational value across samples. The most notable difference is that of self-transcendence, which occurred more strongly in the AR sample than in the CW sample. This finding suggests that the 'worldview' or a universal and benevolent motivational force is

present in the AR sample. Qualitative analysis revealed that worldview is a powerful motivational force, as the wanting to 'make a difference'. This is one of the most notable differences between the AR and CW samples.

The mediating effect of motivation on the relationship between technological propensity and productivity was investigated. The results of this test of mediation revealed that in the case of academic researchers, openness to change does indeed significantly mediate the relationship between technological propensity and productivity. However, this was not the case for crowd-workers. In both samples, self-transcendence, conservation and self-enhancement do not mediate the relationship between technological propensity and productivity. The relationship between innate ability and productivity is discussed next.

6.4.2.4 Innate Ability and Productivity

According to the results of the qualitative analysis, innate ability refers to intelligence, skills and proficiencies that may provide an advantage in the pursuit of BRP. These include i) intelligence, ii) track record and iii) perceptiveness. King and Anderson's (2002) model of innovative performance facilitators includes 'cognitive ability," or a general intelligence factor.

Unlike cognitive ability, innate ability also includes 'track record', which is a record of previous achievements. "*Often the best predictor of the future is the past*" (R21). Individuals that have produced innovative outcomes in the past, will likely produce them again the future. It is likely that innate ability is the product of HCI. In this way, increased levels of education, training and experience will improve productivity. Perceptiveness, or 'big picture thinking' was cited as a powerful driver of BRP. Innate ability was not investigated quantitatively. Instead, HCI, which are considered drivers of innate ability, were considered. Having discussed the internal drivers of productivity, in relation to qualitative and quantitative findings and literature, the external drivers of productivity are now discussed.

6.4.3 External Drivers of Productivity

According to the qualitative findings, external drivers of BRP include HCI, work climate and resource availability. Each of these are now discussed in relation to the qualitative and

quantitative findings and literature. First, the relationship between HCI and productivity is discussed.

6.4.3.1 HCI and Productivity

For Becker (1962), human capital investments are expenditures on training, education, as a form of individual level self-invested capital, and that is directly associated with productivity. Although no specific measurement of HCI was taken for the qualitative sample, many qualitative respondents did advocate the importance of diversity of HCI as it related to training, education and experience in a variety of different fields of study, different schools, colleges and universities and different environmental stimuli during academic development. Qualitative analysis revealed that HCI that contribute to BRP include i) education and experience, ii) support and iii) cross-pollination. Furthermore, it was discovered that the diversity of these investments may further contribute to BRP. Individuals who have accumulated varied forms of education and training will more likely produce BRP. Given the large difference in average ages of the sample, it is assumed that qualitative respondents had significantly higher, and more diverse levels of HCI than respondents in the AR sample. These higher levels of HCI are most likely a contributor to higher levels of productivity and therefore, higher probabilities of producing breakthroughs. The relationship between HCI and technological propensity however, may differ based on personality, motivation and climate, as previously discussed.

The differences in HCI between academic researchers and crowd workers are not comparable since MTurk use is often only part-time and is rarely a full-time career (Goodman, et al. 2013). In contrast, the measurement of years of experience as an academic researcher is reflective of full-time career experience. Crowd workers had an average of 3.13 years on MTurk and academic researchers had an average of 15.54 years of experience as an academic researcher. Crowd-workers were also asked for their level of education, on a scale ranging from primary schooling to PhD.

In the academic context, both productivity and technological propensity may be constrained by ‘innovation gatekeepers’ (Anderson et al., 1998; Callaghan, 2015a). Examples of these are restrictive bureaucracies and conformity to tradition that eschews risk tasking. It is possible that prolonged exposure to restrictive and non-flexible systems may inhibit breakthrough productivity. Therefore, for the AR sample, while HCI and productivity are positively related,

the extent to which innovative output increases or decreases as HCI increases and becomes further diversified over time, is unknown. This presents an opportunity for future research.

The result of regression testing indicates significant differences in the AR and CW samples. In the AR sample, HCI is positively associated with productivity. In the case of crowd-workers however, CWP is not dependent on education or experience. This finding supports Callaghan's (2014a) theory of 6G; that real-time productivity may indeed be possible by harnessing 6G mechanisms that offer economies of scale. For example, crowd-workers can produce large amounts of output in significantly less time without experience or knowledge. It is acknowledged, however, that these measures of output are not comparable. It is necessary that academic researchers spend long periods of time producing journal articles, whereas crowd-workers need only a few minutes or hours to complete an HIT. Notwithstanding these differences, these findings indicate that 6G mechanisms (such as MTurk) may provide a conduit through which some forms of real-time productivity may be enabled. It remains to be seen if the application of 6G to the process of academic research could produce similar results.

Further tests of mediation were conducted. It was found that personality motivation and climate do not mediate the relationship between HCI and productivity, in either sample. The relationship between work climate and productivity is discussed next, as follows.

6.4.3.2 Work Climate and Productivity

The results of the qualitative analysis produced a model of climate that ranges from innovative to non-innovative. According to these findings, work climates that are free, open, flexible and supportive are more likely to produce innovations than work climates that are not. This finding is strongly supported by literature (Scott & Bruce, 1994; Patterson, et al., 2005). In comparison, the Organisational Climate Model (OCM) comprises of four work climate types (Patterson, et al., 2005). Two of the opposing ends of the OCM are the Internal Process Model (IPM) and Open Systems Model (OSM). The IPM is associated with a control orientation and internal focus and is therefore not considered conducive to innovation (Patterson, et al., 2005). Conversely, the OSM is associated with an external focus and a flexible orientation and is therefore considered conducive to innovation (Patterson, et al., 2005). The results of the qualitative analysis revealed a strong support for OSM work climates, rather than IPM work climates. Therefore, working climates that are attuned to flexibility, innovation, outward focus

and reflexivity (Patterson, et al., 2005) may be more conducive to BRP. These type of climates (OSM) tend to have an orientation towards change (King & Anderson, 1995) and respond to both external and internal influences in the wider environment (West & Farr, 1990; West, 2002). This is well suited to BRP, which is premised on an open model of innovation (Callaghan, 2014a; Chesbrough, 2003a). Conversely, those working climates that are inwardly focused with emphases on tradition and formalisation are not considered conducive to BRP (Patterson, et al., 2005). These types of climates are primarily concerned with formal rules and procedures (Hall, 1991; Radaelli, Mura, Spiller & Lettieri, 2011) and tend to value established ways of doing things (Anderson & West, 1998). Since BRP seems related to open-thinking and flexibility, inward-focused (or IPM) climates may not be as conducive to BRP as those that are more open and flexible (OSM). For the CW sample, climate was not measured, since most MTurk users tend to work from home (Goodman, et al, 2013). The analysis of the AR sample shows a relatively even split between IPM and OSM work climate perceptions. Interestingly, the lower-order climate measurement entitled 'innovation and flexibility' produced a significantly low mean score, compared to other climate measurements. This finding suggests that university work environments are generally not perceived as innovative and flexible; a detriment to productivity and particularly BRP. Work climate was also found not mediate the relationship between technological propensity and productivity, nor the relationship between HCI and productivity. The relationship between resource availability and productivity is discussed next, as follows.

6.4.3.1 Resource Availability and Productivity

According to the results of the qualitative analysis, the availability of resources is often a serious constraint to research productivity. Chief amongst these is the availability of financial resources. Research funding is a fundamental driver of research productivity. Financial freedom to pursue research interests is a powerful driver of BRP. The cost of laboratory equipment, staff and experimentation is often prohibitive, particularly in the case of large-scale research projects which may produce radically innovative breakthroughs. Time is another resource that is often in short supply. Efficient time management structures may help alleviate time pressures. Financial pressures however, can only be alleviated by sufficient research funding. The source of these research funds is primarily garnered from traditional research funding institutions. For example, in the USA, the National Science Foundation (NSF) is the primary funder of academic and scientific research. Large-scale, government funded research

programs or experiments are typically not financially constrained, but smaller research projects may have to look to other sources for financial support. Qualitative analysis revealed that private funding offers significant financial opportunities, although this can be difficult to acquire. Despite strong indication amongst qualitative respondents that there is generally a problem related to lack of research funds, no respondents made mention of crowdfunding, or other similar distributing funding mechanisms. According to Palmer and Verhoeven (2016), crowdfunding represents a feasible and readily available opportunity to fund scientific and academic research. The crowdfunding industry has grown exponentially since its inception and is commonly used for entrepreneurial and charitable endeavours. However, despite growing evidence that crowdfunding is uniquely suited to funding academic and scientific research (Roberts, 2017; Palmer & Verhoevn, 2016), this seems to have not yet happened. This may represent an important opportunity for academic researchers, which is not being sufficiently exploited. Having concluded discussion pertaining to the synthesis of qualitative and quantitative results and literature, this chapter is now concluded, as follows.

6.5 CHAPTER CONCLUSION

This chapter provides a discussion of the results of the qualitative and qualitative studies undertaken in this research. First, the results of Study 1 (the qualitative study) were discussed according to the propositions derived from qualitative analysis. Next, the findings of Studies 2 and 3 (the quantitative studies) were discussed according to the hypotheses derived from the literature. Finally, the results of Studies 1, 2 and 3 were contrasted and related to pertinent literature, in a synthesis of qualitative and quantitative findings. The core findings of the qualitative study suggest that breakthrough research productivity (BRP) is driven by various internal and external influences. Internal drivers of BRP include personality, motivation, innate ability and technological propensity. External drivers of BRP include human capital investments, work climates and resource availability. The effectiveness of internal drivers of BRP depends largely on HCI. More specifically, the qualitative findings seem to suggest that HCI *diversity* is an important precursor to BRP. In other words, individuals who have varied education, training and experience and who favour cross-disciplinary collaboration, are more likely to produce BRP. Conversely, the external drivers of BRP are largely dependent on efficient managerial structures and the availability and freedom of financial resources. The findings of the qualitative study seem to suggest that financial constraints inhibit innovation, even amongst some of the most successful scientists in the world.

The findings of the quantitative studies suggest that some new technologies and methodologies that offer significant scale advantages may already be in use, in the academic context, and that these may indeed help to stimulate research productivity. Furthermore, that academic researchers with self-transcendental motivations may be more likely to adopt new processes to enhance their productivity, owing to a recognition of the importance of finding solutions to social problems. Strong evidence of the existence of academic research routinisation was uncovered by lack of association between technological propensity and productivity. Furthermore, little to no association, or mediating effect was discovered between work climate perceptions, technological propensity and productivity. However, it was discovered that some personality characteristics and motivational values configurations are significantly associated with technological propensity. This may be attributable to constraints associated with academic routinisation and innovation failure. HCI were, as expected, found to be positively associated with productivity. However, the effects of personality, motivational values and work climate perceptions do not seem to alter this relationship. For academic researchers, gender and field of study are found to moderate the interrelationships between technological propensity, HCI and productivity. It is argued that these findings extend 6G theory. The assessment of a sample of 'crowd-workers', drawn from Amazon's Mechanical Turk was used to further investigate 6G *in the 6G space.* Several important differences between academic researchers and crowd-workers are uncovered. It is discovered that for crowd-workers, productivity is pursued for more self-serving objectives, rather than for humanitarian objectives that are found to be associated with academic researchers. It is also discovered that in the 6G space, productivity may be homogenous across contexts. This means that individual level difference may not impact the interrelationships between technological propensity, HCI and productivity. This holds important consequences for the potential application of 6G in the academic context. It may be possible that individual-level differentiators that inhibit productivity could potentially be eroded by the application of 6G to the research process. A further summary of this research, its conclusions and recommendations for practice, and for further research is now offered in the final chapter, which now follow.

CHAPTER 7
CONCLUSIONS AND RECOMMENDATIONS

7.1 INTRODUCTION

In this chapter, the research is concluded with a summary of the research undertaken. In the previous chapter, the results of the qualitative and quantitative analyses were discussed in relation to literature, and a synthesis of results was provided and discussed. This chapter extends the previous by providing a summary of this research's objectives and relating them to the findings discussed in the previous chapter. Finally, the implications of the outcomes of this study are discussed, as are recommendations for managerial practice and for further research. The primary research question that this research hopes to address is as follows:

What is the relationship between technological propensity and productivity?

In the context of this research, this relationship was investigated across a spectrum of productivity, ranging from breakthrough research productivity (BRP) to academic research productivity to crowd-worker productivity (CWP). Technological propensity was also examined in these contexts. The term technological propensity is used in this research to describe the extent to which individuals take advantage of new technological and methodological opportunities, which may offer significant scale advantages, and may therefore significantly help improve productivity. The primary example of new technology used in this research is the Internet. The primary examples of new methodologies used in this research are crowdsourcing and crowdfunding. The objective of this research was not a comparison of productivity, but rather a comparison of the relationship between technological propensity and productivity, across contexts. To this end, three interlinking studies, including a qualitative study and two quantitative studies were conducted. From the primary research question, above, several sub-ordinate research questions were derived. Hypotheses and sub-hypotheses were then derived from these sub-ordinate research questions. The sub-ordinate research questions are as follows:

1. What is the relationship between technological propensity and productivity?
2. What is the relationship between Human Capital Investments (HCI) and productivity?
3. What are the interactive effects of gender and field of study on the relationships between technological propensity, HCI and productivity?

It is stressed that the findings of this research do not imply causality. Rather, the combined use of qualitative and quantitative methods is used to provide a holistic analysis of some of the potential relationships surrounding technological propensity and productivity. This chapter is structured as follows. First, an overview of the research objectives is provided. Next, recommendations for managerial practice are made, in relation to the findings. Finally, this chapter is concluded was a summary. The objectives of this research are discussed first, in the form of a summary, as follows.

7.2 SUMMARY OF THE RESEARCH OBJECTIVES

The primary aim of this research was to investigate 6G innovation and its relationship with productivity, at the level of the individual. The relationships around technological propensity and productivity were investigated. This included an investigation of potential individual-level differentiators, which may impact this relationship. These include personality, motivational values, work climate perceptions and human capital investments. The overarching aim of this study was to identify potentially useful measures to implement, in academic and scientific research, that may enhance breakthrough research productivity, and which may ultimately help find solutions to social problems in significantly reduced timeframes. Thus, the objective of this research was to test theory that relates technological propensity, personality, motivational values, work climate perceptions, human capital investments and productivity. A summary of the research findings and recommendations, in relation to the research questions, now follows.

7.3 SUMMARY OF THE FINDINGS AND RECOMMENDATIONS

Through a combined qualitative and quantitative analysis, this research has produced empirical evidence, in the form of statistical associations between the variables under study that either supported or opposed theory. An attempt to answer the research questions was made. It is stressed that while causal relationships cannot be asserted, the testing of theory undertaken in this study provides sufficient evidence to support certain arguments made in this research. The answers to the research questions, in relation to the findings of the qualitative and quantitative studies, are now provided in the next sub-sub-sections.

7.3.1 Research Question A: What is the relationship between Technological Propensity and Productivity?

The relationship between technological propensity and productivity underpins this research. The findings of this research suggest that technological propensity may, to some extent, be related to productivity. However, this relationship differs according to context. According to the results of the qualitative study, the use of some new modes of productivity may enable the production of breakthrough research. The results also suggest however, that technological propensity, as an overall measure, is only associated with productivity under certain conditions. Technological propensity may differ depending on personality types and motivational values. For example, academic researchers who are open to experience may be more likely to adopt new modes of productivity to enhance their research output. Conversely, those who are neurotic are less likely to do so. It was also found that academic researchers who have motivational values attuned to self-transcendence and openness to change are more likely to adopt new modes of productivity to enhance their research output. Those who are motivated by conservation however, are less likely to do so.

The implication of these findings is that technological propensity (or, the proclivity to adopt certain new modes of productivity) may be associated with a social imperative. Some individuals may be able to recognise the potential social advantages associated with the use of crowdsourcing and crowdfunding. It has been argued that the failure to innovate in the face of social problems is unethical (Fenton, et al., 2015). 6G innovation theory purports that the application of certain new modes of productivity, which offer significant scale advantages (such as crowdsourcing and crowdfunding) may enhance the rate at which breakthrough innovations occur, and thereby increasing the rate at which solutions to social problems can be found (Callaghan, 2014a). According to the findings of this research, some individuals experience a desire to produce research that "makes a difference," to help other people and to save human lives. These individuals may be willing to adopt unconventional modes of productivity to do so. Examples cited include the use of crowdsourcing to combat the spread of disease or to find cures to existing medical conditions for which no cures are currently available. This may represent a form of 'prosocial motivation', which according to Grant (2008) is a desire to help others by improving one's work performance. It was also found that technological propensity is significantly associated with self-transcendental motivational values, which are those that are related to universalism and benevolence (Deci, 1976; Schwartz,

1992). In other words, those individuals that are concerned with preserving and enhancing the welfare of others (Schwartz, 1992) may be more likely to adopt unconventional modes of productivity. Thus, on the basis of the results, it is argued that individuals who are driven by self-transcendental motivations are able to recognise that the need for new modes of productivity. Furthermore, such individuals may recognise that certain new modes of productivity enhance the probability of producing breakthrough innovations which in turn, may potentially address social problems.

The relationship between technological propensity and productivity however, is dependent on context. In closed contexts, where tradition, convention and conformity are prevalent, individuals may be less likely to adopt new modes of productivity and will be more likely to 'stick to the tried and tested'. The findings of this research suggest that some elements of the academic journal publication system and the academic research funding system may be examples of closed systems, which have become increasingly less open to novel methods and technologies as time progresses. According to Bornman, et al. (2010), this may be the result of innovation 'gatekeepers'. Individuals who work within these systems may, over time, internalise these same ideals and themselves become closed to new ideas, methods, techniques and technologies. Conversely, it was found that open orientation, or the propensity to engage with and adopt new and unconventional modes of productivity is one of the primary drivers of BRP. Openly oriented individuals are therefore also more likely to advocate the use of crowdsourcing or crowdfunding to enhance research output and to increase the probability of producing breakthroughs. Such individuals are also more likely to recognise the benefits associated with new modes of productivity and may in some cases reject convention in favour of the new and untested. For example, the use of open access journal publication was cited as a potential method of overcoming high levels of rejection from traditional journal publications, since open access publications may not be bound by the same overly-rigid constraints often associated with traditional publications.

The implication of these findings is that the academic journal publication system and the academic research funding system may both to some extent, have become routinised, through emphasis on tradition and convention. It is stressed that this finding does not indicate a state of total 'academic failure' (King & Anderson, 2002). However, it does suggest a notable dearth of funding and publication of *breakthrough, radical* innovations. It is argued that these states of routinisation may be attributable to the problems of knowledge aggregation (Nonaka, 1994;

von Hippel, 2004, Smith, 2010) and fund aggregation (Martin & Scott, 2000; McKenna, 2014). Callaghan (2014a) suggests that crowdsourcing may help to alleviate the problem of knowledge aggregation, while crowdfunding may help to alleviate the problem of fund aggregation. The combination of crowdsourcing and crowdfunding therefore, may represent a new mode of productivity, where significant scale advantages are enabled, and the problems of knowledge and fund aggregation might be overcome. According to the results of this study, both crowdsourcing and crowdfunding may indeed offer such advantages, in the academic research context. Indeed, the results indicate that some forms of 6G innovation have, to some extent, already emerged in certain fields of scientific and academic enquiry. Although in its infancy, it was found that certain forms of crowdsourcing are currently in use. Examples include i) idea competitions (for ideation and idea dissemination), ii) user innovations, iii) data collection and dissemination, iv) the assessment of trends in large online populations and, as previously mentioned v) online journal publications. Despite research that indicates that crowdfunding may offer similar advantages (Palmer & Verhoeven, 2017; Roberts, 2017), crowdfunding seems not to have yet enjoyed the same levels of adoption. It is argued that this represents a significant opportunity that has not yet been seized.

Thus, the relationship between technological propensity and productivity depends on context. However, the findings of this research also show that this relationship may change based on differences in motivational values. Academic researchers who are open to change, or those who are motivated by self-direction and stimulation (Schwartz, 1992) may experience a stronger relationship between technological propensity and productivity. Conversely, crowd-workers who are open to change may experience a weaker relationship between technological propensity and CWP. In both cases, no other motivational values seem to mediate this relationship. This implies that that academic researchers who are motivated by excitement, novelty, stimulation and independent thought may be more likely to adopt 6G mechanisms and may produce more research output than their peers, but crowd-workers who are motivated by the same, may produce less.

The implication of this finding is that motivations may differ in the academic and 6G (specifically MTurk) contexts. It shows that even in the crowd-work context, motivations may be aligned to the nature of the work at hand, rather than a blanket prosocial motivation to help others (Grant, 2008). This suggests that the key to BRP in the academic context may depend on the alignment of motivations. In the academic research context, motivations that are self-

transcendental and open to change are more like to produce BRP than those that are self-enhancing or conservative. It may be possible that motivational values configurations shift depending on the context within which research is conducted.

In conclusion, technological propensity is related to some forms of productivity. However, this relationship is dependent on context. In the academic context, this relationship seems to strengthen significantly if academic researchers are openly oriented, or have motivational values configured to openness to change. Research Question B is discussed next.

7.3.2 Research Question B: What is the relationship between HCI and Productivity?

The findings of this research suggest that HCI are related to productivity. This relationship however, is also context dependent. The results of the testing Research Question A suggest that openly oriented individuals tend to be more open to new experiences and ideas, tend to reject convention and adopt unorthodox modes of productivity. Such individuals are therefore more susceptible to the cross-pollination of ideas and knowledge from various sources. In the context of this research, the accumulation of knowledge, education, training and experience is collectively referred to as human capital investments (HCI). HCI are the intangible investments in human capital that contribute to the appreciation of the individual (Bosma, et al., 2004). Following Becker (1962), investments in human capital contribute to work productivity. The results of the qualitative analysis suggest that HCI *diversity* may in some cases, be a more accurate predictor of breakthrough productivity, than the mere accumulation of HCI. The findings suggest that HCI diversity occurs through the cross-pollination of knowledge, combined with variations in education, training and experience. This finding is also supported by literature. For Black and Lynch (2001, p. 266), "it is not so much *whether* you train the workers, but rather, *what you train the workers in,* that affects productivity".

According to the results of the qualitative analysis, human capital investments do indeed form important precursors to breakthrough research. Early environmental support, education, experience and training all contribute to enhanced ability to generate breakthrough research. More importantly, these contribute to cross-pollination of knowledge and ideas from different sources. This finding echoes the assertion of Smith (2010); that innovation is the product of diverse knowledge interactions, and that this assertion may apply at both the organisational, and individual levels. In the context of these findings, this process is referred to as HCI

diversity, which refers to the extent of variation inherent to HCI accumulation. Individuals that switch between institutions, faculties, fields or countries acquire more diverse sources of HCI. The more diverse one's HCI, the greater the probability of producing research breakthroughs. The findings also suggest that female scientists, and scientists from developing countries are more likely to acquire diverse HCI than their counterparts. This is because individuals from developing countries are more likely to pursue education and experience outside of their home countries and home institutions, leading to more varied sources of knowledge and higher rates of knowledge cross-pollination. For Leahey (2006), female scientists or academics tend to specialise less than their male counterparts. This may be attributable to the effects of family life spill-overs. For this reason, female scientists or academics may have more varied research foci and may therefore accumulate knowledge from more varied sources. HCI diversity is not a strict prerequisite for breakthrough research productivity, but it may help to enhance the probability of breakthrough research productivity.

According to the results of the quantitative analyses, HCI is indeed significantly associated with academic research productivity. Those academic researchers who have accumulated more experience will inadvertently have higher levels of research productivity or, will have published more journal articles, over time. This finding is supported by literature. Black and Lynch (2001) suggest that education, training and experience are positive contributors to productivity. However, the extent to which this output is radically innovative is unknown. This is because it is likely that the measurement of journal publications over times is most likely not an accurate reflection of radical innovativeness, rather simply a measurement of output over time.

In the case of crowd-workers however, it was found that education (a form of HCI) is not significantly associated with crowd-work productivity. This means that in the 6G space, education may not be a prerequisite for high levels of productivity. This differs from the academic research context, where as previously discussed, it was found that HCI is a powerful predictor of research productivity. This finding is opposed to the assertions of Black and Lynch (2001). This however, this is most likely because this study was conducted in the 6G space (i.e. online), rather than in an organisational work environment. Therefore, this finding may support 6G theory, which purports that real-time productivity may indeed be enabled through the use of 6G mechanisms such as crowdsourcing (Callaghan, 2014a). Without experience, crowd-workers can produce large amounts of output in significantly less time, whereas academic

researchers spend long periods of time producing journal articles. Again, the quantity of crowd-work output is not a reflection of its' radical innovativeness. Neither is the measurement journal articles over time, as a measure of academic research output. Both are simply measurements of solution-seeking outputs, over time. However, the rate at which crowd-work output is produced far outstrips that of academic research output. In some cases, large scale crowdsourced projects can be completed in real-time (Torr-Brown, 2013). It can be concluded therefore, that 6G mechanisms (such as crowdsourcing) may provide a channel through which some forms of real-time productivity can be enabled. If this process of real-time productivity could be transposed to academic research, there may arise significant increases in the problem-solving potential of academic research, and ultimately, immeasurable social benefits for the world.

The implication of these findings is that HCI is indeed related to breakthrough research productivity, and to academic research productivity. However, HCI is not related to crowd-work productivity. To re-iterate Black and Lynch (2001, p. 266), "it is not so much *whether* you train the workers, but rather, *what you train the workers in,* that affects productivity". 'What you train the workers in' reflects the importance of HCI diversity. HCI is significantly associated with academic researcher productivity, regardless of its innovativeness. But HCI is also associated with radically innovative, *breakthrough* research productivity. In non-crowd contexts, BRP is unlikely to occur without a substantial quantity of human capital investments. However, following the findings of the qualitative analysis, the quality of human capital investments may be as, if not more important than the quantity of human capital investments. Cross-pollination of knowledge, ideas and information is a critical component of BRP. In crowd contexts however, the requirements of HCI and HCI diversity may become void. Large, online crowds of people can perform tasks and complete projects regardless of HCI, or HCI diversity. This finding echoes the assertion of Surowiecki (2004); that it is the *composition of the crowd itself*, rather than the individuals that make up the crowd, that determine the crowd's problem-solving potential. This finding shows the potential of decentralised, probabilistic systems of knowledge. If these traits could be harnessed and applied in the academic research context, the probability of producing radically innovative breakthrough innovations might increase at an exponential rate. Research Question C is discussed next.

7.3.3 Research Question C: What are the interactive effects of gender and field of study on the relationships between technological propensity, HCI and productivity?

The interactive effects of gender and field of study on the relationships between technological propensity, HCI and productivity, were investigated. Analyses were conducted to further test theory that predicted these relationships. The results of the qualitative analysis seem to suggest that gender and field of study may moderate the relationship between technological propensity and productivity. Examination of moderation plots generated from the AR analysis seem to suggest that gender and field of study may moderate the relationships between technological propensity, HCI and productivity. However, the only significant moderation effect is that of gender on the relationship between HCI and productivity. According to this finding, men tend to have higher rates of productivity than women, at both low and high levels of HCI. In the crowd-worker analysis however, it was found that both gender and profession do not significantly moderate the relationships between technological propensity, HCI and productivity (or CWP). Examination of the moderation plots generated from the CW analysis seem to confirm this finding.

These findings may provide indication that in the 6G space, individual-level productivity may become homogenous across gender and professional boundaries. Previously, it was also found that differences in education (HCI) may also become mitigated in crowd contexts. In the context of academic research however, individual level differences (such as gender) may introduce disparities in productivity. The findings related to Research Questions A and B show that almost no mediating effect from the introduction of personality, motivational values (excluding openness to change) and climate perceptions. Therefore, individual level differentiators seem to have very little influence on the major variables under study on this research, in the context of both academic researchers and crowd-workers. However, the results of the tests of moderation provide clarity as to the primary differences between these two samples. Given the non-significant results of moderation testing in the CW analysis, it may be possible that in the 6G space, a 'homogenising' effect takes place. This notion is supported by theory relating to the wisdom of crowds. For Surowiecki (2004), individual level differences in education, gender and profession may become mitigated at the aggregate crowd level. Instead, each individual crowd-worker's unique skills, knowledge and expertise are 'plugged in' where they are needed, to ultimately erode the problem space (Callaghan, 2015c). This, in turn, reflects the assertion of Smith (2010): the more diverse the crowd, the more likely breakthrough productivity will be generated. This also represents an opportunity for further research; on the potential homogenising effect that may occur in the 6G space. The implications

of the findings of this research are now discussed. Managerial recommendations that stem from these implications are also made, in the section that follows.

7.4. CONTRIBUTIONS OF THE STUDY

This research sought to contribute novel perspectives on i) the productivity of academic researchers, ii) the innovative (or 'breakthrough') productivity of academic researchers and iii) the extent to which innovative academic research might sufficiently address the needs of societal stakeholders. Attempts to make these contributions were made by investigating the relationship between technological propensity and productivity, across three different contexts.

It is argued that this research is important for the following reasons. Firstly, in a context where returns to investment in research and R&D may be constrained (Anderson, de Dreu & Nijstadt, 2002; Nielsen, 2012), this research seeks to offer a novel perspective on possible new modes of productivity which could potentially increase the rate at which academic research output is produced (Brabham, 2008; Torr-Brown, 2013). By leveraging the scale advantages associated with these new modes of productivity, it may be possible to exponentially enhance returns to investment in academic research (Avital, 2011; Woolley, Aggarwal & Malone, 2015). Therefore, this research seeks to make an important contribution to the theory surrounding academic research productivity.

Secondly, as previously noted, quantitative measures of academic research productivity may not be indicative of the inherent innovativeness of academic research output (Anderson, de Dreu & Nijstad, 2002; Camanario, 2009; Alvesson & Sandberg, 2013). Often, academic researchers may seek to produce academic research output which is inherently 'safe', in that its content may conform to traditional, 'routinised' paradigms associated with its field, in the interest of legitimacy and normalisation (Kuhn, 1970; Kortum, 1997; Gordon, 2012). However, the adoption and application of certain new modes of productivity, such as crowdsourcing, have been shown to produce significantly improved problem-solving capabilities (Surowiecki, 2004; Nielsen, 2012), and innovative potential (Howe, 2006; Brabham, 2013), by drawing on the collective intelligence of large, diverse, geographically dispersed, online crowds of individuals (Woolley, et al, 2010; Malone, Lauchaber & Dellarocas, 2010). Given the numerous examples of success in the context of industrial R&D (e.g. InnoCentive, FoldIt and the Polymath Project), it is argued that the adoption and application of these processes to the

academic research process may not only exponentially increase academic research output but may also exponentially increase the inherent innovativeness of academic research output. Therefore, this research also seeks to make an important contribution to theory surrounding academic innovation.

Thirdly and finally, given the moral issues associated with academic research that does not sufficiently address the needs of societal stakeholders, the development and testing of theory regarding the use of new scalable research methodologies may provide important insight into the potentialities of innovative academic research that addresses the needs of societal stakeholders. It is argued that this research is critical, in a global context where academic research has been accused of becoming increasingly routinised (Anderson, de Dreu & Nijstad, 2002) and of insufficiently addressing the needs of societal stakeholders (Fenton, Chillag & Michael, 2015).

7.5 IMPLICATIONS, RECOMMENDATIONS FOR FURTHER RESEARCH AND MANAGERIAL RECOMMENDATIONS

This research has attempted to offer a detailed investigation of 6G theory, and its relationship to productivity, across three different contexts. It is argued that the implications of these findings are important. This is because the findings suggest that 6G innovation may provide the means through which the routinisation of academic research (Anderson, et al., 2004; Bornman, et al., 2010) might be addressed, across global contexts. Several implications derive from these findings. These implications, and recommendations based on the findings, are discussed in the following sections, below.

7.5.1 Some academic research systems may have become routinised, but this can be addressed

The findings of this research suggest that academic research may indeed, in some cases be constrained by convention and traditionalism, where risky endeavors are eschewed in favour of the pursuit of safer, incremental innovations and "adding-to-the-literature contributions" (Alvesson & Sandberg, 2013, p. 28). Radical innovations may not be pursued because they are associated with a high degree of risk and may often involve the use of unconventional modes of productivity. This may result in paradigmatic stagnation, where established norms and

boundary conditions become set, and very difficult to change, despite evidence that new paradigms and modes of productivity may produce improved results (Torr-Brown, 2013; Palmer & Verhoeven, 2017). 6G innovation (crowdsourcing and crowdfunding) may represent a radical change, that is expected to be met with resistance (Christensen, 1997; Christensen, Raynor & McDonald, 2015). It is possible that 6G innovation represents a new iteration of Schumpeterian 'creative destruction' and may therefore eventually replace current modes of productivity, in the future. Indeed, this is evidenced by the finding that some forms of 6G have already emerged and are already in use. However, resistance to the further spread of 6G innovation in the academic research context seems prevalent. It is therefore argued that these findings support the assertions of Kuhn (1970); that the progress of science is a function of paradigmatic change, and that paradigmatic stagnation may inadvertently result in a state of 'non-innovativeness', or routinisation (Anderson, et al., 2004). It is also stressed, however, that academic research is not entirely non-innovative, but that incremental innovations seem to be generally preferred over those that are radical. According to the research findings, these symptoms of routinisation seem to have occurred in the academic journal publication system and academic research funding system.

It is suggested that further research is required to investigate the extent to which the implementation and adoption of 6G innovation may overcome paradigmatic stagnation (or, routinisation), in this context. Given the successes of some forms of crowdsourcing, described above, it is recommended that other forms of 6G innovation be adopted and implemented in cases where paradigmatic stagnation is prevalent. Crowdfunding, in particular, may provide significant opportunities in the funding of academic research (Palmer & Verhoeven, 2017). The publication of research on open-source, online journal articles may also offer significant advantages. Further research is needed to assess the potential of these new methodologies in the academic context.

7.5.2 6G innovation may be associated with a social imperative

The findings of this research suggest that the adoption of some forms of 6G innovation may offer positive social externalities, by providing a means to address large-scale social problems in significantly reduced time frames. Some individuals, in academic and crowd contexts, seem able to recognise this potential. Ideally, those in positions of management should aspire to instill self-transcendental values into group, faculty, laboratory, or institutional cultures.

Following Radder (2010) and Fenton, et al., (2015), there exists a moral incentive to pursue research that produces socially beneficial outcomes. If successful, the adoption of certain unconventional modes of productivity may result in improved radically innovative performance. As a result, this may contribute to the prevention of the catastrophic outcomes of certain global social problems, perhaps even loss of human life (Callaghan, 2017a; Wu, 2017).

7.5.3 Motivational values differ in academic and 6G spaces

Different motivational values configurations may impact the relationships around technological propensity and productivity, according to context. MTurk users (crowd-workers) were found to have different values configurations characteristics to academic researchers. Crowd-workers generally favour self-enhancement value configurations over self-transcendental values configurations. Thus, despite functioning within the 6G space, the work undertaken on MTurk may act as an impediment to the desire to produce socially-beneficial output. It remains to be seen if academic researchers functioning within the 6G space would maintain self-transcendental values configurations or resort to more self-enhancing configurations. This presents an opportunity for further research. It is evident however, that academic researchers that have motivational values related to conservation, are unlikely to seek unconventional modes of productivity. It was also found that for academic researchers that are open to change are more willing to adopt 6G innovation and thereby, produce more output. It is therefore recommended that managers seek to instill self-transcendental and open values, in academic researchers, rather than conservation and self-enhancement values. In doing so, the probability of adopting unconventional modes of productivity may increase, as might the probability of producing more output. Following probabilistic theory, the greater the degree of academic research output, the greater the probability of producing radical, breakthrough innovations. As previously mentioned, this study is conducted at the level of the individual. It is hoped that these findings may form a foundation upon which to assess 6G innovation at the greater group, or organisational levels, in future 6G research.

7.5.4 Diversity versus homogenisation in the 6G space

In the 6G space, differences in gender and profession do not seem to significantly impact the relationships between technological propensity, HCI and productivity. This suggests a possible ‘homogensation’ effect, where individual-level differentiators (such as gender, profession and

education) may become nullified, at the level of the aggregate crowd. One possible explanation for this is that crowd-work imitates naturally-occurring, complex, biological systems, such as swarms of bees. In these types of systems, performance is a reliant on overall trends of entire populations, rather than individuals or small groups. In the qualitative analysis however, attention was drawn to HCI diversity. Individuals who have more diverse educations, who come from more diverse backgrounds, or who have more varied training, experience and education, are more likely to adopt unconventional modes of productivity and are highly likely to produce research breakthroughs.

These findings may seem incongruous, since HCI diversity is purported to contribute to BRP, but such differences may become mitigated in the 6G space. It would follow then, that crowd-work would be converse to the requirements of BRP. However, it is argued that even though some individual differences may be mitigated at the aggregate level of the crowd, specialised and diversified skills and abilities of individual crowd-members, are still imperative to the production of innovation. Therefore, diversity may not be a function of biographical characteristics, such as gender, profession or nationality, but rather a function of the diversity of one's education, training and experience. As in naturally occurring collectives, the productivity of the crowd may not be dependent on the individual but is dependent on the collective. Conversely, the breakthrough, radically innovative potential of the crowd is not based on the diversity of the collective, but the diversity of individuals. This finding represents an opportunity for further research. Specifically, research that investigates the makeup of online crowds, and the relationships around HCI, HCI diversity and productivity.

7.5.5 The relationships between BRP, academic research productivity and CWP: managerial recommendations

One of the objectives of this research was to investigate potential ways to stimulate breakthrough research productivity, in the context of academic research. The findings of this research bear important implications for academic research. In some cases, the problems of knowledge and fund aggregation may prevent the production of breakthrough research. The findings of this study suggest that this can be overcome, and BRP can be stimulated, by implementing certain managerial practices.

At the extreme end of the academic research spectrum, it was found that BRP is driven by a combination of internal and external drivers. At an optimal configuration of these drivers, it may be possible to streamline the research process, and ultimately produce more radical innovations. One of the most essential findings is that the diversity of these drivers, particularly HCI, may further increase the probability of producing breakthrough radical innovations. However, the extent to which BRP can be pursued is also dependent on individual differences, such as personality and motivational values. Personalities that are open, extraverted and conscientiousness are more likely to produce BRP, than those that are agreeable or neurotic. Motivational values that are related to openness to change and self-transcendentalism are more likely to produce BRP, than those that are conservative or self-enhancing. Recommendations for management and for future research are discussed next.

7.6. RECOMMENDATIONS FOR MANAGEMENT AND FOR FUTURE RESEARCH

It is recommended that managers seek to foster work climates, or work environments, that are conducive to these types of personalities and motivations. The findings of this study suggest that Open Systems Models of work climate are better suited to innovation than Internal Process Models of work climate. Furthermore, individuals that perceive their work climates to be outwardly focused (rather than inwardly focused), are more likely to adopt and implement unconventional modes of productivity and may therefore stand a greater probability of producing BRP. Management should strive to encourage flexibility, openness and collaboration, and should also strive to remove bureaucratic restrictions and regulations, to the fullest possible extent. In this way, innovation may be fostered. Cross-department, cross-faculty and cross-institutional collaboration should be stimulated to maximise knowledge interactions, and the subsequent probability of producing breakthroughs. Management should also seek to streamline the efficient and effective flow of resources, financial and otherwise. A lack of resource availability can be detrimental to the production of BRP. Management should look to take this role upon themselves, which may help to alleviate time pressures on individual academic researchers and help to simulate freedom and flexibility.

The findings of the crowd-worker analysis suggest that the adoption and implementation of 6G innovation methodologies (i.e. online crowdsourcing) may enable advantages of scale and homogenisation, each of which were previously discussed, above. Furthermore, in this context, real-time productivity may be enabled, where problems might be solved as they emerge. Some

forms of 6G innovation have already emerged, and are already in use, in the academic context. These include data collection and analysis, collaboration and open source, online publication. It is recommended that these be further investigated, and actively pursued. It is stressed again that 6G innovation methods (such as crowdsourcing and crowdfunding) are not considered replacements for conventional methods of research. Rather, that they may be useful complementary methods, which may help to enhance the probability of producing research breakthroughs. There exist notable differences between the 6G and academic research contexts. For this reason, further research is required to investigate the extent to which these interventions are indeed applicable to the context of academic research. However, given the findings of this research, some 6G innovation methods, such as crowdsourcing and crowdfunding, do indeed seem to offer unique opportunities to help improve the probability of producing breakthrough research outputs, which may help to address important social problems. This concludes the section on implications and recommendations for management, and for further research. The conclusion of this chapter now follows.

7.6 CHAPTER CONCLUSION

In this chapter, the results of the process of hypothesis testing undertaken in this research were summarised and a discussion of the managerial implications of the results of this research was provided. Recommendations for management and for further research were also made. Each of the research questions was answered by assessing the outcomes of the qualitative and quantitative analyses. Some of the theory of 6G innovation is supported by the findings of this study. New technologies and methodologies (such as the Internet, and crowdsourcing and crowdfunding, respectively) that offer significant economies of scale, may indeed hold the potential to accelerate and enhance the rate at which radical, breakthrough innovations occur. This finding is, to some extent, generalisable to both the global and South African academic research contexts. The following are the primary conclusions of this research.

First, the academic journal publication system and the academic research funding system may in some cases have become routinised. In other words, these may in some cases have become standardised to the point where change is rejected in favour of the traditional and conventional. However, some new ‘Sixth Generation’ technologies, techniques and methodologies, or those associated with crowdsourcing, open innovation and crowdfunding over the Internet do indeed currently exist in the academic research context, and are gradually becoming more

commonplace and acceptable in academic research. These may hold significant potential to reverse the effects of routinisation. However, the adoption and implementation of these methodologies may prove difficult, owing to the restrictive nature of certain paradigmatic standards, which seem to have become commonplace. If it is possible to overcome this resistance however, significant advantages may be enabled.

Second, 6G innovation may be related to a prosocial imperative. It has been argued that academic researchers face a moral incentive to pursue research that produces social externalities. It has also been argued that 6G innovation methods, such as crowdsourcing and crowdfunding offer unique opportunities to find solutions to pressing social problems and may thereby fulfill this incentive. According to the findings of this study, individuals with self-transcendental motivations are more likely recognise the potential of 6G methodologies, such as crowdsourcing and crowdfunding, to find solutions to pressing social problems. Such individuals are also more likely to adopt these methodologies, and according to 6G theory, therefore also more likely to produce breakthrough innovations that may help to address social problems.

Third, motivational values differ across academic and 6G contexts. Academic researchers tend to have motivational values configured to self-transcendentalism, while crowd-workers tend to have motivational values configured to self-enhancement. For academic researchers, the relationship between conservation and technological propensity is negative, while for crowd-workers, this relationship is positive. For academic researchers, openness to change positively mediates the relationship between technological propensity and productivity, but this does not occur in the case of crowd-workers. It may be possible that these differences are attributable to context. Further research is required to investigate if academic researcher motivational values would change, in 6G contexts.

Fourth, diversity and homogenisation in the 6G space are not mutually exclusive conditions. In the 6G space, there may exist a ‘homogenising’ effect, in which individual-level differences in gender, profession and values configurations may be mitigated. This may due to the inherent nature of large online collectives, which configure, integrate and apply knowledge inputs to problem spaces, in a naturally efficient and effective manner. While individual differences may be negated in the 6G space, this does not impact the ability of an individual to generate breakthrough, radical innovations. Instead, abilities and skills may be a function of human

capital investments that are *diverse*. Individuals who have more diverse backgrounds, education, training and experience, may internalise the benefits of cross-pollination of knowledge, ideas, information and collaboration, and therefore possess a higher propensity to produce breakthrough research. Essentially, the diversity of crowds may be related to the diversity of each individual crowd-member's HCI, rather than the diversity of biographical differences.

Fifth, and finally, findings related to BRP and CWP may be useful in the academic research context. There exist several drivers of BRP and CWP, which could potentially be transposed to the academic research context, to help increase the probability of producing research breakthroughs. Certain individual differences such as personality and motivational values are conducive to producing breakthroughs, while others are not. Certain external drivers, such as work climates and resource availability may also influence BRP. Although further research is required, the advantages of crowd-work also offers some potential applications in academic research, to improve performance and reduce time frames.

It is argued that these results contribute to and extend 6G innovation theory. If 6G innovation has indeed already emerged in the context of academic research, then future implementation and adoption of 6G practice may be possible, despite the impediments associated with routinisation. It is also argued therefore, that this research has made an important contribution to academic routinisation theory and has provided cross-sectional insight into the state of academic research journal publication and academic research funding, in the South African academic research context and to a lesser extent, in the context of notable scientific award-winners.

The empirical findings of this research are taken to be relatively generalisable to the South African academic research context. This is because the academic researcher sample comprised respondents from nine major South African universities, dispersed geographically across the country. It is acknowledged, however, that these results suggest generalisability to university contexts only, and not to private or commercial R&D, or to university contexts in other countries. The empirical findings relating to the crowd-worker sample are also taken to be relatively generalisable to the MTurk context since the crowd-worker sample is diverse and represents a rough demographic composition of MTurk (Goodman et al., 2013). However, these findings are not taken to be generalisable in the broad sense of 6G, since crowd-workers

operating on InnoCentive, KickStarter and other 6G-type platforms are not considered synonymous with MTurk crowd-workers. The findings of the qualitative study are also not taken to be generalisable in the context of award winning, globally renowned scientists, academics and researchers, since the sample used in this research represents only a small portion of some of the major scientific and academic awards that exist. Nevertheless, owing to the diversity of the qualitative sample, it is argued that these findings do to some extent provide a glimpse into the state of academic and scientific research, in the global context.

In summary, the findings of this research suggest that despite certain constraints, there seems to exist a general trend towards 6G in the academic research context. Further adoption of 6G in this context may trigger probabilistic effects in knowledge aggregation, which could potentially enhance the radical-innovativeness of research output and potentially provide solutions to important social problems that have not yet been solved. Based on the findings of this study, managerial recommendations were made. It is recommended that some of the primary drivers of productivity in these contexts be transposed to the context of academic research. If these are applied and managed efficiently and effectively, the probability of generating breakthrough, radical innovations may increase, exponentially, and solutions to some of the world's most pressing social problems may be found. It is also recommended that further research is undertaken, to investigate the specific and causal mechanisms of breakthrough research productivity, and of crowd-work productivity, and their relationship to academic research productivity. Furthermore, it is recommended that investigations of the potential of 6G in the commercial, or industrial R&D contexts, are also undertaken.

6G theory may represent a new paradigm of the management of problem solving and may be well-suited to the context of academic research, if certain barriers can be overcome. If so, 6G research offers exciting opportunities to address social problems that have failed to be solved thus far. It is therefore hoped that this research has provided a glimpse into a future, where people from across the world are able to work together for the betterment of humanity.

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9. APPENDIX

9.1. Reporting of Further Statistical Tests (EFAs)

9.1. Reporting of Further Statistical Tests

Further statistical tests were conducted, to provide insight into the methodological processes applied in this study. The factor structures of the TIPI scale (Gosling & Swan, 2003) used to measure the FFM (Costa & McCrae, 1990), Schwartz's (1992) motivational values, the Organisational Climate Model (OCM) (Patterson, et al., 2005) and the technological propensity scale, which was derived from literature were all tested by way of exploratory factor analyses. Section 8.1.1 reports the results of testing of the factor structure of the FFM dimensions in the context of this study. In Section 8.1.2 the results of the factor analysis of the Schwartz values dimensions are reported. In Section 8.1.3 the results of the organisational climate model are reported. In Section 8.1.4. the factor structure of the technological propensity scale is reported.

9.1.1.1. Modified TIPI Rotated Factor Matrix (AR Sample)

	Factors							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
E1						.584		
C1			.677					
N1	.679							
O1								
A2				.631				
E3						.583		
C3			.578					
N3	.785							
O3								
A4				.479				
E5								
A5				.613				
C5			.695					
N5	.520							
O5								
A1							.478	
E2		.781						
C2								.500
N2								-.510
O2					.946			
A3							.406	
E4		.798						
C4								
N4	.447							
O4								

Extraction method: Principal Axis Factoring

Rotation Method: Varimax with Kaiser normalization

Rotation converged in 12 iterations.

Factor score below .400 are suppressed.

9.1.1.1. Modified TIPI Rotated Factor Matrix (CW Sample)

	Factors					
	1	**2**	**3**	**4**	**5**	**6**
E1			.625			
C1		.716				
N1	-.856					
O1				.533		
A2					.726	
E3			.706			
C3		.731				
N3	-.806					

O3				.658		
A4					.610	
E5			.461	.425		
A5		.423			.503	
C5		.662				
N5	-.424					
O5				.678		
A1	.569					
E2			.790			
C2	.453	.479				
N2	-.488	-.478				
O2				.421		.610
A3	.523					
E4			.714			
C4						.477
N4		-.426				
O4						.548

Extraction method: Principal Axis Factoring

Rotation Method: Varimax with Kaiser normalization

Rotation converged in 12 iterations.

Factor score below .400 are suppressed.

9.1.2.1. PVQ Rotated Factor Matrix (AR Sample)

	Factors				
	1	**2**	**3**	**4**	**5**
Self-Direction 1					.528
Power 1					
Universalism 1			.461		
Achievement 1				.746	
Security 1	.654				
Stimulation 1		.497			.438
Conformity 1	.618				
Universalism 2			.514		
Tradition 1			.426		
Hedonism 1		.673			
Self-Direction 2					
Benevolence 1			.667		
Achievement 2				.702	
Security 2	.516				
Stimulation 2		.634			
Conformity 2	.669				
Power 2				.637	
Benevolence 2			.576		
Universalism 3			.490		
Tradition 2	.463				
Hedonism 2		.838			

Extraction method: Principal Axis Factoring

Rotation Method: Varimax with Kaiser normalization

Rotation converged in 7 iterations.

Factor score below .400 are suppressed.

9.1.2.1. PVQ Rotated Factor Matrix (CW Sample)

	Factors		
	1	**2**	**3**
Self-Direction 1	.559	.435	
Power 1		.571	
Universalism 1	.768		
Achievement 1		.573	
Security 1	.476		.534
Stimulation 1		.627	
Conformity 1			.639
Universalism 2	.739		
Tradition 1	.630		
Hedonism 1		.518	
Self-Direction 2	.689		
Benevolence 1	.699		
Achievement 2		.661	
Security 2			.544
Stimulation 2		.719	
Conformity 2			.692
Power 2		.507	.440
Benevolence 2	.681		
Universalism 3	.661		
Tradition 2			.570
Hedonism 2		.610	

Extraction method: Principal Axis Factoring

Rotation Method: Varimax with Kaiser normalization

Rotation converged in 7 iterations.

Factor score below .400 are suppressed.

9.1.3. Organisational Climate Model (OCM) Rotated Factor Matrix (AR Sample)

	Factors					
	1	**2**	**3**	**4**	**5**	**6**
Reflexivity 1	.594					
Reflexivity 2	.532					
Tradition 4						
Innovation & Flexibility 4			.617			
Innovation & Flexibility 3			.699			
Formailsation 3				.499		
Innovation and Flexibility 5	.611					

Innovation & Flexibility 1	.679					
Formalisation 1				.499		
Reflexivity 3	.624					
Innovation & Flexibility 2			.688			
Innovation & Flexibility 6	.425					
Tradition 2		-.566				
Formalisation 4				-.520		
Reflexivity 4					.562	
Tradition 3		-.458				
Reflexivity 5					.531	
Tradition 1		-.488				
Outward Focus 5					.533	
Formalisation 5				.609		
Outward Focus 1						
Outward Focus 2		.702				
Outward Focus 3		.649				
Formalisation 2				.537		
Outward Focus 4		.562				

Extraction method: Principal Axis Factoring

Rotation Method: Varimax with Kaiser normalization

Rotation converged in 10 iterations.

Factor score below .400 are suppressed.

9.1.4.1 Technological Propensity Component Matrix (AR Sample)

	Factors					
	1	**2**	**3**	**4**	**5**	**6**
Tolerance for Disruption 1					.523	
Crowd Propensity 1						.587
Open Orientation 1	.421		.567			
Tolerance for Disruption 2	.474					
Crowd Propensity 2						
Collaborative Propensity 2	.417					-.405
Technology Use 3			-.449			
Tolerance for Disruption 4	.436			-.412		
Technology Use 4		.588				
Crowd Propensity 4		.693				
Open Orientation 4	.491					
Collaborative Propensity 4	.730					
Technology Use 1				.625		
Collaborative Propensity 1	.516					
Technology Use 2					.531	
Open Orientation 2	.610					
Tolerance for Disruption 3						.417
Crowd Propensity 3			.401			
Open Orientation 3						.506

Collaborative Propensity 3	.696					

Extraction method: Principal Component Analysis

6 components extracted.

Factor score below .400 are suppressed.

9.1.4.2 Technological Propensity Component Matrix (CW Sample)

	Factors				
	1	**2**	**3**	**4**	**5**
Tolerance for Disruption 1	.429	-.432			
Crowd Propensity 1	.444			-.485	
Open Orientation 1	.587				
Tolerance for Disruption 2	.504				
Crowd Propensity 2	.577				
Collaborative Propensity 2	.592				
Technology Use 3	.650				
Tolerance for Disruption 4	.535				
Technology Use 4	.469				
Crowd Propensity 4	.597		.456		
Open Orientation 4	.580				
Collaborative Propensity 4	.532	.440			
Technology Use 1				.571	
Collaborative Propensity 1					-.520
Technology Use 2					.496
Open Orientation 2			.470		
Tolerance for Disruption 3		.459			
Crowd Propensity 3		.576			
Open Orientation 3		.599			
Collaborative Propensity 3			.607		

Extraction method: Principal Component Analysis

5 components extracted.

Factor score below .400 are suppressed.

9.2. Results (Tables)

SPSS output generated by tests of regression are now reported, according to the hypothesis tested. The tables generated during the AR analysis are reported first, followed by the tables generated during the CW analysis. Only the results of the primary research questions are provided for the CW analysis. The following abbreviations are used in the AR analysis tables.

Gender	1 = male
Nationality1	1 = South African
Nationality2	1 = not South African
Language1	1 = English
Language2	2 = Afrikaans
Language3	1 = Other South African languages
Language 4	1 = foreign languages
Field1	1 = Commerce, Law & Management
Field 2	1 = Sciences
Field 3	1 = Humanities
Field 5	1 = Health Sciences
Years	Total years of experience as an academic researcher
Marital Status	1 = marries
Children	Number of dependent children
PersA	Agreeableness
PersE	Extraversion
PersC	Conscientiousness
PersO	Openness to Experience
PersN	Neuroticism
MotST	Self-Transcendence

MotOC	Openness to Change
MotC	Conservation
MotSE	Self-Enhancement
ClimIPM	Internal Process Model (IPM)
ClimOSM	Open Systems Model (OSM)
TFD	Tolerance for Disruption
TP	Technology Use
CCP	Crowd propensity
OO	Open Orientation
CP	Collaborative Propensity

9.2.1 Hypothesis A1: Technological propensity is associated with productivity (AR sample)

9.2.1.1 Coefficients and Collinearity Diagnostics

Coefficients[a]											
Model		**Unstandardised Coefficients**		**Standardised Coefficients**	**t**	**Sig.**	**Correlations**			**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Zero-order**	**Partial**	**Part**	**Tolerance**	**VIF**
1	(Constant)	1.020	.539		1.891	.059					
	Gender	.254	.121	.110	2.099	.037	.211	.109	.101	.839	1.192
	Nat1SA	-.145	.129	-.056	-1.122	.263	-.110	-.058	-.054	.934	1.071
	Lan1Eng	.237	.124	.100	1.903	.058	.104	.099	.092	.843	1.187
	Lan3OtherSA	-.138	.286	-.026	-.484	.629	-.077	-.025	-.023	.781	1.281
	Children	.027	.049	.029	.559	.577	-.009	.029	.027	.880	1.137
	Field2	.050	.140	.020	.359	.720	.187	.019	.017	.727	1.375

	Field3	-.409	.136	-.161	-3.002	.003	-.204	-.155	-.145	.802	1.246
	Years	.021	.005	.208	3.963	.000	.280	.203	.191	.841	1.189
	ClimIPM	-.191	.128	-.078	-1.488	.137	-.031	-.077	-.072	.843	1.187
	ClimOSM	-.277	.126	-.117	-2.204	.028	-.081	-.114	-.106	.825	1.212
2	(Constant)	.326	.695		.470	.639					
	Gender	.261	.121	.113	2.159	.032	.211	.112	.104	.838	1.193
	Nat1SA	-.122	.130	-.047	-.941	.347	-.110	-.049	-.045	.922	1.084
	Lan1Eng	.233	.124	.098	1.876	.061	.104	.098	.090	.842	1.187
	Lan3OtherSA	-.117	.285	-.022	-.411	.681	-.077	-.021	-.020	.779	1.283
	Children	.028	.049	.029	.570	.569	-.009	.030	.027	.880	1.137
	Field2	.044	.140	.018	.317	.751	.187	.017	.015	.727	1.376
	Field3	-.403	.136	-.159	-2.961	.003	-.204	-.153	-.142	.802	1.247
	Years	.021	.005	.215	4.087	.000	.280	.209	.196	.835	1.197
	ClimIPM	-.189	.128	-.077	-1.478	.140	-.031	-.077	-.071	.843	1.187
	ClimOSM	-.279	.125	-.118	-2.223	.027	-.081	-.115	-.107	.825	1.212
	Technological propensity	.204	.129	.077	1.578	.115	.072	.082	.076	.973	1.028

a. Dependent variable: productivity

9.2.1.2 Bootstrap Coefficients

Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	1.020	.005	.529	.058	.018	2.151
	Gender	.254	.001	.121	.037	.022	.496
	Nat1SA	-.145	-.010	.140	.308	-.446	.102
	Lan1Eng	.237	-.002	.127	.058	-.003	.487
	Lan3OtherSA	-.138	-.005	.295	.632	-.697	.453
	Children	.027	.003	.049	.593	-.062	.127
	Field2	.050	-.007	.155	.740	-.264	.357
	Field3	-.409	-.002	.130	.001	-.655	-.147
	Years	.021	.000	.005	.002	.010	.031
	ClimIPM	-.191	-.002	.132	.147	-.458	.059
	ClimOSM	-.277	.001	.133	.036	-.521	-.005
2	(Constant)	.326	-.008	.627	.595	-.879	1.624
	Gender	.261	.001	.121	.037	.026	.503
	Nat1SA	-.122	-.009	.141	.394	-.424	.130
	Lan1Eng	.233	-.002	.127	.068	-.010	.486
	Lan3OtherSA	-.117	-.004	.290	.673	-.678	.467
	Children	.028	.003	.049	.584	-.062	.124
	Field2	.044	-.006	.155	.772	-.276	.349
	Field3	-.403	-.002	.130	.001	-.654	-.136
	Years	.021	.000	.005	.001	.011	.032
	ClimIPM	-.189	-.001	.129	.137	-.448	.063
	ClimOSM	-.279	.001	.131	.034	-.514	-.008
	Technological Propensity	.204	.003	.121	.101	-.038	.452

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

9.2.2. Hypothesis A2.1: Openness to Experience is significantly associated with technological propensity (AR sample)

9.2.2.1. Coefficients and Collinearity Diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.189	.059		19.985	.000					
	Gender	-.017	.014	-.063	-1.220	.223	-.064	-.059	-.059	.871	1.148
	Nat1SA	-.033	.015	-.109	-2.206	.028	-.104	-.107	-.106	.948	1.054
	Lan1Eng	.002	.015	.009	.167	.867	.001	.008	.008	.840	1.191
	Lan3OtherSA	-.017	.030	-.032	-.584	.560	-.029	-.028	-.028	.758	1.319
	Children	6.100E-5	.006	.001	.011	.991	-.008	.001	.001	.870	1.150
	Field2	.011	.017	.035	.632	.528	.022	.031	.030	.737	1.356
	Field3	-.008	.016	-.026	-.496	.620	-.037	-.024	-.024	.822	1.217
	Years	-.001	.001	-.088	-1.688	.092	-.078	-.082	-.081	.847	1.180
	ClimIPM	.005	.014	.019	.382	.703	.009	.019	.018	.890	1.124
	ClimOSM	.006	.014	.022	.424	.672	.013	.021	.020	.882	1.133
2	(Constant)	1.127	.064		17.682	.000					
	Gender	-.014	.014	-.051	-.996	.320	-.064	-.049	-.048	.864	1.157
	Nat1SA	-.033	.015	-.109	-2.229	.026	-.104	-.108	-.107	.948	1.054
	Lan1Eng	.003	.014	.012	.221	.825	.001	.011	.011	.839	1.192
	Lan3OtherSA	-.010	.030	-.019	-.341	.733	-.029	-.017	-.016	.751	1.331
	Children	.000	.006	.002	.049	.961	-.008	.002	.002	.869	1.150
	Field2	.008	.017	.026	.466	.641	.022	.023	.022	.734	1.362
	Field3	-.013	.016	-.043	-.813	.417	-.037	-.040	-.039	.809	1.235
	Years	-.001	.001	-.102	-1.955	.051	-.078	-.095	-.093	.839	1.193
	ClimIPM	.003	.014	.011	.211	.833	.009	.010	.010	.886	1.129
	ClimOSM	.006	.014	.024	.466	.642	.013	.023	.022	.882	1.133
	PersO	.014	.006	.127	2.584	.010	.118	.125	.124	.949	1.054

a. Dependent variable: Technological propensity

9.2.2.2. Bootstrap Coefficients

Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	1.189	-.001	.068	.001	1.053	1.322
	Gender	-.017	-6.195E-6	.014	.220	-.045	.011
	Nat1SA	-.033	.000	.015	.032	-.065	-.004
	Lan1Eng	.002	.000	.015	.870	-.028	.033
	Lan3OtherSA	-.017	-.001	.031	.566	-.076	.039
	Children	6.100E-5	.000	.006	.994	-.011	.011
	Field2	.011	-.001	.017	.512	-.022	.043
	Field3	-.008	.000	.017	.628	-.041	.026
	Years	-.001	-2.011E-6	.001	.098	-.002	.000
	ClimIPM	.005	.001	.017	.785	-.028	.037
	ClimOSM	.006	.000	.015	.709	-.022	.038
2	(Constant)	1.127	-.001	.068	.001	.998	1.256
	Gender	-.014	.000	.014	.315	-.042	.014
	Nat1SA	-.033	.000	.015	.029	-.064	-.005
	Lan1Eng	.003	.000	.015	.833	-.026	.033
	Lan3OtherSA	-.010	-.001	.031	.728	-.071	.050
	Children	.000	.000	.005	.962	-.011	.011
	Field2	.008	-.001	.016	.626	-.025	.039
	Field3	-.013	.000	.017	.437	-.047	.019
	Years	-.001	2.177E-6	.001	.054	-.002	2.897E-5
	ClimIPM	.003	.001	.017	.874	-.031	.034
	ClimOSM	.006	.001	.015	.677	-.021	.038
	PersO	.014	-7.066E-5	.006	.010	.004	.026

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

9.2.3. Hypothesis A2.2: Extraversion is significantly associated with technological propensity (AR sample)

9.2.3.1. Coefficients and Collinearity Diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.189	.059		19.985	.000					
	Gender	-.017	.014	-.063	-1.220	.223	-.064	-.059	-.059	.871	1.148
	Nat1SA	-.033	.015	-.109	-2.206	.028	-.104	-.107	-.106	.948	1.054
	Lan1Eng	.002	.015	.009	.167	.867	.001	.008	.008	.840	1.191
	Lan3OtherSA	-.017	.030	-.032	-.584	.560	-.029	-.028	-.028	.758	1.319
	Children	6.100E-5	.006	.001	.011	.991	-.008	.001	.001	.870	1.150
	Field2	.011	.017	.035	.632	.528	.022	.031	.030	.737	1.356
	Field3	-.008	.016	-.026	-.496	.620	-.037	-.024	-.024	.822	1.217
	Years	-.001	.001	-.088	-1.688	.092	-.078	-.082	-.081	.847	1.180
	ClimIPM	.005	.014	.019	.382	.703	.009	.019	.018	.890	1.124
	ClimOSM	.006	.014	.022	.424	.672	.013	.021	.020	.882	1.133
2	(Constant)	1.179	.063		18.828	.000					
	Gender	-.016	.014	-.058	-1.107	.269	-.064	-.054	-.053	.841	1.189
	Nat1SA	-.033	.015	-.108	-2.175	.030	-.104	-.106	-.105	.946	1.057
	Lan1Eng	.002	.015	.008	.157	.875	.001	.008	.008	.839	1.192
	Lan3OtherSA	-.016	.030	-.030	-.542	.588	-.029	-.026	-.026	.753	1.327
	Children	.000	.006	-.001	-.022	.982	-.008	-.001	-.001	.866	1.155
	Field2	.011	.017	.035	.630	.529	.022	.031	.030	.737	1.356
	Field3	-.008	.016	-.025	-.476	.634	-.037	-.023	-.023	.821	1.219
	Years	-.001	.001	-.091	-1.728	.085	-.078	-.084	-.083	.838	1.193
	ClimIPM	.005	.014	.018	.348	.728	.009	.017	.017	.885	1.129
	ClimOSM	.006	.014	.022	.420	.675	.013	.020	.020	.882	1.133
	PersE	.002	.005	.024	.490	.625	.037	.024	.024	.944	1.059

a. Dependent variable: technological propensity

9.2.3.2. Bootstrap Coefficients

Bootstrap for Coefficients							
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	1.189	.000	.070	.001	1.052	1.325
	Gender	-.017	.000	.014	.216	-.045	.007
	Nat1SA	-.033	-2.411E-5	.015	.026	-.061	-.002
	Lan1Eng	.002	-.001	.014	.865	-.026	.030
	Lan3OtherSA	-.017	-.001	.029	.562	-.076	.033
	Children	6.100E-5	-2.996E-5	.006	.992	-.011	.011
	Field2	.011	.001	.016	.540	-.022	.041
	Field3	-.008	.001	.017	.622	-.041	.027
	Years	-.001	-3.100E-5	.001	.079	-.002	3.838E-5
	ClimIPM	.005	-5.366E-5	.018	.754	-.030	.040
	ClimOSM	.006	.000	.015	.686	-.023	.035
2	(Constant)	1.179	.000	.073	.001	1.029	1.328
	Gender	-.016	.000	.014	.247	-.042	.009
	Nat1SA	-.033	5.112E-5	.015	.029	-.061	-.003
	Lan1Eng	.002	-.001	.014	.868	-.026	.030
	Lan3OtherSA	-.016	-.001	.029	.581	-.075	.037
	Children	.000	-5.826E-5	.006	.984	-.012	.010
	Field2	.011	.001	.016	.547	-.022	.041
	Field3	-.008	.001	.017	.634	-.040	.028
	Years	-.001	-3.168E-5	.001	.072	-.002	3.372E-5
	ClimIPM	.005	-9.586E-5	.017	.776	-.030	.038
	ClimOSM	.006	.000	.015	.697	-.023	.035
	PersE	.002	.000	.005	.610	-.007	.012

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

9.2.4. Hypothesis A2.3: Conscientiousness is significantly associated with technological propensity (AR sample)

9.2.4.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.189	.059		19.985	.000					
	Gender	-.017	.014	-.063	-1.220	.223	-.064	-.059	-.059	.871	1.148
	Nat1SA	-.033	.015	-.109	-2.206	.028	-.104	-.107	-.106	.948	1.054
	Lan1Eng	.002	.015	.009	.167	.867	.001	.008	.008	.840	1.191
	Lan3OtherSA	-.017	.030	-.032	-.584	.560	-.029	-.028	-.028	.758	1.319
	Children	6.100E-5	.006	.001	.011	.991	-.008	.001	.001	.870	1.150
	Field2	.011	.017	.035	.632	.528	.022	.031	.030	.737	1.356
	Field3	-.008	.016	-.026	-.496	.620	-.037	-.024	-.024	.822	1.217
	Years	-.001	.001	-.088	-1.688	.092	-.078	-.082	-.081	.847	1.180
	ClimIPM	.005	.014	.019	.382	.703	.009	.019	.018	.890	1.124
	ClimOSM	.006	.014	.022	.424	.672	.013	.021	.020	.882	1.133
2	(Constant)	1.172	.064		18.457	.000					
	Gender	-.016	.014	-.061	-1.173	.242	-.064	-.057	-.056	.868	1.152
	Nat1SA	-.033	.015	-.108	-2.183	.030	-.104	-.106	-.105	.948	1.055
	Lan1Eng	.002	.015	.007	.136	.892	.001	.007	.007	.838	1.193
	Lan3OtherSA	-.017	.030	-.031	-.560	.576	-.029	-.027	-.027	.757	1.320
	Children	.000	.006	.001	.026	.979	-.008	.001	.001	.869	1.151
	Field2	.009	.017	.030	.534	.594	.022	.026	.026	.726	1.377
	Field3	-.009	.016	-.029	-.550	.583	-.037	-.027	-.026	.817	1.223
	Years	-.001	.001	-.090	-1.717	.087	-.078	-.084	-.083	.846	1.182
	ClimIPM	.006	.014	.021	.405	.686	.009	.020	.019	.889	1.125
	ClimOSM	.006	.014	.023	.444	.657	.013	.022	.021	.882	1.134
	PersC	.003	.004	.037	.745	.457	.039	.036	.036	.965	1.037

a. Dependent variable: technological propensity

9.2.4.2. Bootstrap coefficients

Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	1.189	.000	.068	.001	1.055	1.318
	Gender	-.017	.000	.014	.209	-.044	.010
	Nat1SA	-.033	.001	.014	.023	-.061	-.004
	Lan1Eng	.002	-.001	.015	.874	-.027	.032
	Lan3OtherSA	-.017	-.001	.030	.567	-.081	.039
	Children	6.100E-5	-4.781E-5	.006	.994	-.011	.011
	Field2	.011	.000	.016	.506	-.021	.041
	Field3	-.008	-8.710E-5	.017	.637	-.041	.025
	Years	-.001	2.152E-5	.001	.076	-.002	.000
	ClimIPM	.005	.000	.017	.758	-.026	.038
	ClimOSM	.006	-.001	.015	.688	-.025	.036
2	(Constant)	1.172	.000	.070	.001	1.033	1.308
	Gender	-.016	.000	.014	.227	-.044	.010
	Nat1SA	-.033	.001	.014	.025	-.061	-.005
	Lan1Eng	.002	-.001	.015	.881	-.028	.031
	Lan3OtherSA	-.017	-.001	.030	.581	-.080	.040
	Children	.000	-6.904E-5	.006	.975	-.011	.011
	Field2	.009	.000	.016	.571	-.023	.040
	Field3	-.009	-3.869E-5	.017	.594	-.042	.024
	Years	-.001	2.203E-5	.001	.073	-.002	.000
	ClimIPM	.006	.000	.017	.745	-.026	.038
	ClimOSM	.006	-.001	.015	.685	-.025	.036
	PersC	.003	-3.854E-6	.004	.449	-.005	.012

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

9.2.5. Hypothesis A2.4: Agreeableness is significantly associated with technological propensity (AR sample)

9.2.4.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.189	.059		19.985	.000					
	Gender	-.017	.014	-.063	-1.220	.223	-.064	-.059	-.059	.871	1.148
	Nat1SA	-.033	.015	-.109	-2.206	.028	-.104	-.107	-.106	.948	1.054
	Lan1Eng	.002	.015	.009	.167	.867	.001	.008	.008	.840	1.191
	Lan3OtherSA	-.017	.030	-.032	-.584	.560	-.029	-.028	-.028	.758	1.319
	Children	6.100E-5	.006	.001	.011	.991	-.008	.001	.001	.870	1.150
	Field2	.011	.017	.035	.632	.528	.022	.031	.030	.737	1.356
	Field3	-.008	.016	-.026	-.496	.620	-.037	-.024	-.024	.822	1.217
	Years	-.001	.001	-.088	-1.688	.092	-.078	-.082	-.081	.847	1.180
	ClimIPM	.005	.014	.019	.382	.703	.009	.019	.018	.890	1.124
	ClimOSM	.006	.014	.022	.424	.672	.013	.021	.020	.882	1.133
2	(Constant)	1.197	.062		19.171	.000					
	Gender	-.017	.014	-.065	-1.247	.213	-.064	-.061	-.060	.866	1.154
	Nat1SA	-.033	.015	-.110	-2.215	.027	-.104	-.107	-.107	.948	1.055
	Lan1Eng	.003	.015	.010	.192	.848	.001	.009	.009	.836	1.195
	Lan3OtherSA	-.018	.030	-.034	-.615	.539	-.029	-.030	-.030	.753	1.328
	Children	3.699E-5	.006	.000	.006	.995	-.008	.000	.000	.869	1.150
	Field2	.011	.017	.036	.640	.523	.022	.031	.031	.737	1.357
	Field3	-.008	.016	-.026	-.492	.623	-.037	-.024	-.024	.822	1.217
	Years	-.001	.001	-.084	-1.571	.117	-.078	-.076	-.076	.814	1.228
	ClimIPM	.006	.014	.021	.405	.686	.009	.020	.019	.887	1.128
	ClimOSM	.006	.014	.023	.445	.656	.013	.022	.021	.880	1.137
	PersA	-.002	.005	-.021	-.413	.680	-.024	-.020	-.020	.924	1.082

a. Dependent variable: Technological propensity

9.2.4.2. Bootstrap coefficients

Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	1.189	.001	.069	.001	1.057	1.327
	Gender	-.017	.000	.014	.217	-.044	.010
	Nat1SA	-.033	-5.406E-5	.015	.029	-.062	-.004
	Lan1Eng	.002	-.001	.015	.871	-.027	.032
	Lan3OtherSA	-.017	.000	.031	.577	-.081	.041
	Children	6.100E-5	-8.855E-5	.005	.993	-.011	.010
	Field2:Sciences	.011	.000	.017	.518	-.024	.044
	Field3:Humanities	-.008	.000	.017	.643	-.041	.025
	Years	-.001	2.774E-5	.001	.087	-.002	.000
	ClimIPM	.005	-.001	.017	.753	-.028	.036
	ClimOSM	.006	.000	.015	.688	-.023	.037
2	(Constant)	1.197	.000	.068	.001	1.070	1.337
	Gender	-.017	.000	.014	.209	-.044	.010
	Nat1SA	-.033	-2.472E-5	.015	.028	-.062	-.004
	Lan1Eng	.003	-.001	.015	.850	-.027	.033
	Lan3OtherSA	-.018	.000	.031	.553	-.082	.041
	Children	3.699E-5	-8.491E-5	.006	.996	-.011	.010
	Field2:Sciences	.011	.000	.017	.511	-.024	.044
	Field3:Humanities	-.008	.000	.017	.651	-.040	.026
	Years	-.001	2.296E-5	.001	.115	-.002	.000
	ClimIPM	.006	-.001	.017	.739	-.028	.037
	ClimOSM	.006	.000	.015	.670	-.023	.038
	PersA	-.002	.000	.005	.642	-.012	.008

a. Unless otherwise noted, bootstrap results are based on 10000 bootstrap samples.

9.2.6. Hypothesis A2.5 Neuroticism is significantly associated with technological propensity (AR sample)

9.2.6.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.189	.059		20.017	.000					
	Gender	-.017	.014	-.063	-1.220	.223	-.064	-.059	-.059	.871	1.148
	Nat1SA	-.033	.015	-.109	-2.206	.028	-.104	-.107	-.106	.948	1.054
	Lan1Eng	.002	.015	.009	.167	.867	.001	.008	.008	.840	1.191
	Lan3OtherSA	-.017	.030	-.032	-.584	.560	-.029	-.028	-.028	.758	1.319
	Children	6.100E-5	.006	.001	.011	.991	-.008	.001	.001	.870	1.150
	Field2	.011	.017	.035	.632	.528	.022	.031	.030	.737	1.356
	Field3	-.008	.016	-.026	-.496	.620	-.037	-.024	-.024	.822	1.217
	Years	-.001	.001	-.088	-1.688	.092	-.078	-.082	-.081	.847	1.180
	ClimIPM	.005	.014	.019	.382	.703	.009	.019	.018	.890	1.124
	ClimOSM	.006	.014	.022	.424	.672	.013	.021	.020	.882	1.133
2	(Constant)	1.234	.063		19.641	.000					
	Gender	-.019	.014	-.070	-1.364	.173	-.064	-.066	-.065	.867	1.153
	Nat1SA	-.033	.015	-.108	-2.187	.029	-.104	-.106	-.105	.948	1.055
	Lan1Eng	.005	.015	.017	.327	.744	.001	.016	.016	.835	1.198
	Lan3OtherSA	-.019	.030	-.035	-.638	.524	-.029	-.031	-.031	.758	1.320
	Children	-.001	.006	-.012	-.231	.818	-.008	-.011	-.011	.858	1.165
	Fiel	.011	.017	.038	.676	.500	.022	.033	.032	.737	1.357
	Field3:Humanities	-.006	.016	-.019	-.357	.721	-.037	-.017	-.017	.818	1.222
	Years	-.001	.001	-.104	-1.977	.049	-.078	-.096	-.095	.831	1.204
	ClimIPM	.005	.014	.018	.361	.718	.009	.018	.017	.889	1.124
	ClimOSM	.005	.014	.020	.388	.698	.013	.019	.019	.882	1.134
	PersN	-.012	.006	-.105	-2.130	.034	-.085	-.103	-.102	.938	1.066

a Dependent Variable: Technological propensity

9.2.6.2. Bootstrap coefficients

Bootstrap for Coefficients							
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	1.189	.002	.070	.001	1.044	1.328
	Gender	-.017	.000	.013	.219	-.043	.009
	Nat1SA	-.033	-.001	.015	.020	-.062	-.005
	Lan1Eng	.002	.000	.015	.885	-.028	.032
	Lan3OtherSA	-.017	-.001	.031	.557	-.082	.040
	Children	6.100E-5	8.677E-5	.006	.998	-.011	.011
	Field2	.011	.000	.016	.510	-.020	.041
	Field3	-.008	.000	.016	.642	-.039	.026
	Years	-.001	7.157E-6	.001	.098	-.002	.000
	ClimIPM	.005	-.001	.017	.760	-.031	.040
	ClimOSM	.006	.000	.015	.687	-.024	.035
2	(Constant)	1.234	.002	.071	.001	1.091	1.377
	Gender	-.019	.000	.013	.181	-.045	.007
	Nat1SA	-.033	.000	.015	.019	-.061	-.005
	Lan1Eng	.005	.000	.015	.743	-.025	.035
	Lan3OtherSA	-.019	.000	.030	.513	-.083	.039
	Children	-.001	7.643E-5	.006	.820	-.013	.010
	Field2	.011	.000	.016	.501	-.018	.042
	Field3	-.006	.000	.016	.752	-.036	.028
	Years	-.001	7.575E-6	.001	.051	-.002	2.568E-5
	ClimIPM	.005	-.001	.017	.769	-.030	.039
	ClimOSM	.005	.000	.015	.706	-.024	.034
	PersN	-.012	-1.563E-5	.006	.047	-.023	.000

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

9.2.7. Hypothesis A3.1: Self-Transcendence is significantly associated with technological propensity (AR Sample)

9.2.7.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3.336	.188		17.743	.000					
	Gender	-.053	.044	-.062	-1.212	.226	-.065	-.059	-.058	.871	1.148
	Nat1SA	-.106	.048	-.109	-2.214	.027	-.104	-.107	-.107	.948	1.054
	Lan1Eng	.007	.046	.008	.161	.872	.000	.008	.008	.840	1.191
	Lan3OtherSA	-.053	.094	-.031	-.565	.572	-.027	-.028	-.027	.758	1.319
	Children	.000	.018	-.001	-.010	.992	-.009	.000	.000	.870	1.150
	Field2	.038	.053	.040	.722	.471	.023	.035	.035	.737	1.356
	Field3	-.018	.050	-.019	-.357	.721	-.031	-.017	-.017	.822	1.217
	Years	-.003	.002	-.093	-1.782	.075	-.082	-.087	-.086	.847	1.180
	ClimIPM	.013	.045	.015	.294	.769	.007	.014	.014	.890	1.124
	ClimOSM	.013	.044	.015	.288	.774	.006	.014	.014	.882	1.133
2	(Constant)	2.733	.247		11.060	.000					
	Gender	-.024	.044	-.029	-.555	.579	-.065	-.027	-.026	.844	1.185
	Nat1SA	-.101	.047	-.105	-2.155	.032	-.104	-.105	-.102	.948	1.055
	Lan1Eng	.013	.045	.015	.286	.775	.000	.014	.014	.839	1.192
	Lan3OtherSA	-.080	.093	-.047	-.865	.388	-.027	-.042	-.041	.753	1.327
	Children	.000	.018	.000	.007	.994	-.009	.000	.000	.870	1.150
	Field2	.058	.052	.062	1.120	.263	.023	.055	.053	.729	1.371
	Field3	-.016	.050	-.017	-.328	.743	-.031	-.016	-.016	.822	1.217
	Years	-.004	.002	-.100	-1.950	.052	-.082	-.095	-.092	.846	1.182
	ClimIPM	.028	.045	.032	.632	.528	.007	.031	.030	.882	1.134
	ClimOSM	.006	.044	.007	.148	.882	.006	.007	.007	.881	1.135
	MotST	.110	.030	.182	3.688	.000	.174	.177	.175	.919	1.088

a Dependent Variable: Technological propensity

9.2.7.2. Bootstrap coefficients

Bootstrap for Coefficients							
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	3.336	-.015	.220	.001	2.883	3.763
	Gender	-.053	-.003	.042	.213	-.140	.026
	Nat1SA	-.106	-6.086E-5	.048	.026	-.197	-.009
	Lan1Eng	.007	-.001	.047	.855	-.086	.098
	Lan3OtherSA	-.053	-.002	.093	.563	-.245	.131
	Children	.000	-.001	.017	.991	-.036	.033
	Field2	.038	.001	.052	.464	-.058	.146
	Field3	-.018	.004	.053	.714	-.117	.089
	Years	-.003	-7.614E-5	.002	.061	-.007	9.672E-5
	ClimIPM	.013	.003	.056	.820	-.092	.127
	ClimOSM	.013	.003	.048	.803	-.078	.116
2	(Constant)	2.733	-.027	.303	.001	2.126	3.303
	Gender	-.024	-.002	.041	.563	-.107	.054
	Nat1SA	-.101	-.001	.046	.030	-.189	-.008
	Lan1Eng	.013	.000	.046	.764	-.080	.101
	Lan3OtherSA	-.080	-.003	.091	.382	-.269	.102
	Children	.000	-.001	.017	.994	-.034	.033
	Field2	.058	.002	.052	.254	-.036	.168
	Field3	-.016	.004	.052	.731	-.114	.088
	Years	-.004	-6.962E-5	.002	.043	-.007	.000
	ClimIPM	.028	.004	.059	.655	-.084	.143
	ClimOSM	.006	.003	.049	.897	-.088	.109
	MotST	.110	.002	.031	.001	.051	.175

a. Unless otherwise noted, bootstrap results are based on 10000 bootstrap samples.

9.2.8. Hypothesis A3.2: Openness to change is significantly associated with technological propensity (AR Sample)

9.2.8.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3.336	.188		17.743	.000					
	Gender	-.053	.044	-.062	-1.212	.226	-.065	-.059	-.058	.871	1.148
	Nat1SA	-.106	.048	-.109	-2.214	.027	-.104	-.107	-.107	.948	1.054
	Lan1Eng	.007	.046	.008	.161	.872	.000	.008	.008	.840	1.191
	Lan3OtherSA	-.053	.094	-.031	-.565	.572	-.027	-.028	-.027	.758	1.319
	Children	.000	.018	-.001	-.010	.992	-.009	.000	.000	.870	1.150
	Field2	.038	.053	.040	.722	.471	.023	.035	.035	.737	1.356
	Field3	-.018	.050	-.019	-.357	.721	-.031	-.017	-.017	.822	1.217
	Years	-.003	.002	-.093	-1.782	.075	-.082	-.087	-.086	.847	1.180
	ClimIPM	.013	.045	.015	.294	.769	.007	.014	.014	.890	1.124
	ClimOSM	.013	.044	.015	.288	.774	.006	.014	.014	.882	1.133
2	(Constant)	2.735	.200		13.690	.000					
	Gender	-.019	.042	-.022	-.443	.658	-.065	-.022	-.020	.858	1.165
	Nat1SA	-.088	.045	-.091	-1.936	.054	-.104	-.094	-.089	.945	1.058
	Lan1Eng	.015	.044	.017	.343	.732	.000	.017	.016	.839	1.192
	Lan3OtherSA	-.144	.090	-.085	-1.599	.111	-.027	-.078	-.073	.741	1.349
	Children	.003	.017	.007	.150	.881	-.009	.007	.007	.869	1.151
	Field2	.033	.050	.035	.666	.506	.023	.032	.030	.737	1.356
	Field3	-.022	.048	-.023	-.451	.652	-.031	-.022	-.021	.822	1.217
	Years	-.003	.002	-.072	-1.441	.150	-.082	-.070	-.066	.844	1.185
	ClimIPM	-.001	.043	-.001	-.020	.984	.007	-.001	-.001	.887	1.127
	ClimOSM	.002	.042	.002	.040	.968	.006	.002	.002	.881	1.135
	MotOC	.152	.023	.319	6.747	.000	.315	.313	.309	.937	1.067

a. Dependent variable: technological propensity

9.2.8.2. Bootstrap coefficients

Bootstrap for Coefficients							
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	3.336	-.005	.211	.001	2.896	3.745
	Gender	-.053	-.001	.043	.202	-.144	.033
	Nat1SA	-.106	.001	.047	.026	-.192	-.008
	Lan1Eng	.007	.001	.049	.880	-.092	.109
	Lan3OtherSA	-.053	.001	.093	.555	-.250	.122
	Children	.000	.000	.018	.994	-.038	.034
	Field2	.038	.002	.053	.485	-.068	.142
	Field3	-.018	.000	.053	.742	-.117	.082
	Years	-.003	.000	.002	.068	-.007	.000
	ClimIPM	.013	-.001	.054	.810	-.099	.119
	ClimOSM	.013	.001	.048	.799	-.082	.106
2	(Constant)	2.735	-.008	.219	.001	2.294	3.151
	Gender	-.019	.000	.041	.646	-.101	.061
	Nat1SA	-.088	.001	.045	.042	-.172	.002
	Lan1Eng	.015	.002	.046	.744	-.077	.105
	Lan3OtherSA	-.144	-.001	.099	.144	-.357	.039
	Children	.003	.000	.017	.885	-.030	.037
	Field2	.033	.002	.051	.513	-.067	.131
	Field3	-.022	.002	.050	.661	-.116	.075
	Years	-.003	.000	.002	.150	-.006	.001
	ClimIPM	-.001	-.001	.050	.985	-.103	.094
	ClimOSM	.002	.001	.045	.976	-.084	.095
	MotOC	.152	.001	.023	.001	.108	.198

a. Unless otherwise noted, bootstrap results are based on 10000 bootstrap samples.

9.2.9. Hypothesis A3.3: Conservation is significantly associated with technological propensity (AR Sample)

9.2.9.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3.336	.188		17.743	.000					
	Gender	-.053	.044	-.062	-1.212	.226	-.065	-.059	-.058	.871	1.148
	Nat1SA	-.106	.048	-.109	-2.214	.027	-.104	-.107	-.107	.948	1.054
	Lan1Eng	.007	.046	.008	.161	.872	.000	.008	.008	.840	1.191
	Lan3OtherSA	-.053	.094	-.031	-.565	.572	-.027	-.028	-.027	.758	1.319
	Children	.000	.018	-.001	-.010	.992	-.009	.000	.000	.870	1.150
	Field2	.038	.053	.040	.722	.471	.023	.035	.035	.737	1.356
	Field3	-.018	.050	-.019	-.357	.721	-.031	-.017	-.017	.822	1.217
	Years	-.003	.002	-.093	-1.782	.075	-.082	-.087	-.086	.847	1.180
	ClimIPM	.013	.045	.015	.294	.769	.007	.014	.014	.890	1.124
	ClimOSM	.013	.044	.015	.288	.774	.006	.014	.014	.882	1.133
2	(Constant)	3.754	.205		18.322	.000					
	Gender	-.045	.043	-.053	-1.047	.296	-.065	-.051	-.049	.870	1.150
	Nat1SA	-.083	.047	-.085	-1.760	.079	-.104	-.086	-.083	.937	1.067
	Lan1Eng	-.013	.045	-.014	-.281	.779	.000	-.014	-.013	.832	1.202
	Lan3OtherSA	.000	.092	.000	.004	.997	-.027	.000	.000	.746	1.340
	Children	.002	.018	.007	.136	.892	-.009	.007	.006	.869	1.151
	Field2	.013	.052	.014	.254	.799	.023	.012	.012	.729	1.371
	Field3	-.058	.050	-.061	-1.161	.246	-.031	-.057	-.055	.797	1.255
	Years	-.005	.002	-.130	-2.517	.012	-.082	-.122	-.118	.827	1.209
	ClimIPM	-.002	.044	-.002	-.044	.965	.007	-.002	-.002	.885	1.131
	ClimOSM	.035	.044	.041	.806	.421	.006	.039	.038	.872	1.147
	MotC	-.102	.022	-.235	-4.606	.000	-.201	-.219	-.216	.848	1.179

a Dependent Variable: Technological propensity

9.2.9.2. Bootstrap coefficients

Bootstrap for Coefficients							
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	3.336	.005	.217	.001	2.928	3.772
	Gender	-.053	-.001	.043	.216	-.140	.030
	Nat1SA	-.106	.001	.047	.031	-.196	-.014
	Lan1Eng	.007	.000	.046	.867	-.086	.097
	Lan3OtherSA	-.053	-.004	.092	.562	-.242	.118
	Children	.000	.001	.018	.992	-.033	.036
	Field2	.038	.002	.052	.455	-.060	.148
	Field3	-.018	-.002	.053	.734	-.126	.082
	Years	-.003	-4.116E-6	.002	.073	-.007	.000
	ClimIPM	.013	.000	.055	.806	-.096	.122
	ClimOSM	.013	-.003	.048	.777	-.087	.101
2	(Constant)	3.754	.004	.241	.001	3.287	4.234
	Gender	-.045	-.001	.042	.289	-.132	.035
	Nat1SA	-.083	.001	.048	.084	-.177	.013
	Lan1Eng	-.013	.000	.045	.763	-.104	.076
	Lan3OtherSA	.000	-.005	.093	.993	-.190	.177
	Children	.002	.001	.018	.891	-.031	.039
	Field2	.013	.002	.051	.796	-.086	.122
	Field3	-.058	-.003	.053	.280	-.166	.049
	Years	-.005	-1.732E-5	.002	.011	-.008	-.001
	ClimIPM	-.002	.000	.056	.971	-.113	.107
	ClimOSM	.035	-.003	.047	.448	-.065	.122
	MotC	-.102	.000	.024	.001	-.148	-.052

a. Unless otherwise noted, bootstrap results are based on 10000 bootstrap samples.

9.2.10. Hypothesis A3.4: Self-enhancement is significantly associated with technological propensity (AR Sample)

9.2.10.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3.336	.188		17.743	.000					
	Gender	-.053	.044	-.062	-1.212	.226	-.065	-.059	-.058	.871	1.148
	Nat1SA	-.106	.048	-.109	-2.214	.027	-.104	-.107	-.107	.948	1.054
	Lan1Eng	.007	.046	.008	.161	.872	.000	.008	.008	.840	1.191
	Lan3OtherSA	-.053	.094	-.031	-.565	.572	-.027	-.028	-.027	.758	1.319
	Children	.000	.018	-.001	-.010	.992	-.009	.000	.000	.870	1.150
	Field2	.038	.053	.040	.722	.471	.023	.035	.035	.737	1.356
	Field3	-.018	.050	-.019	-.357	.721	-.031	-.017	-.017	.822	1.217
	Years	-.003	.002	-.093	-1.782	.075	-.082	-.087	-.086	.847	1.180
	ClimIPM	.013	.045	.015	.294	.769	.007	.014	.014	.890	1.124
	ClimOSM	.013	.044	.015	.288	.774	.006	.014	.014	.882	1.133
2	(Constant)	3.343	.202		16.548	.000					
	Gender	-.053	.044	-.063	-1.212	.226	-.065	-.059	-.058	.871	1.148
	Nat1SA	-.105	.048	-.109	-2.200	.028	-.104	-.107	-.106	.944	1.059
	Lan1Eng	.007	.046	.008	.156	.876	.000	.008	.008	.838	1.194
	Lan3OtherSA	-.052	.094	-.031	-.555	.579	-.027	-.027	-.027	.753	1.328
	Children	.000	.018	.000	-.009	.993	-.009	.000	.000	.869	1.150
	Field2	.038	.053	.040	.716	.474	.023	.035	.035	.736	1.359
	Field3	-.018	.050	-.019	-.357	.721	-.031	-.017	-.017	.822	1.217
	Years	-.003	.002	-.094	-1.778	.076	-.082	-.086	-.086	.834	1.199
	ClimIPM	.013	.045	.015	.297	.767	.007	.014	.014	.889	1.125
	ClimOSM	.013	.044	.015	.284	.776	.006	.014	.014	.881	1.134
	MotSE	-.002	.020	-.005	-.094	.925	-.003	-.005	-.005	.941	1.063

a Dependent Variable: technological propensity

9.2.10.2. Bootstrap coefficients

Bootstrap for Coefficients							
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	3.336	-.004	.220	.001	2.899	3.789
	Gender	-.053	-.002	.043	.227	-.136	.029
	Nat1SA	-.106	.001	.050	.026	-.202	-.010
	Lan1Eng	.007	-.002	.046	.855	-.086	.096
	Lan3OtherSA	-.053	.000	.093	.561	-.254	.107
	Children	.000	.000	.018	.998	-.035	.034
	Field2	.038	.002	.053	.475	-.067	.140
	Field3	-.018	.001	.056	.750	-.126	.098
	Years	-.003	9.352E-5	.002	.093	-.007	.000
	ClimIPM	.013	.001	.054	.810	-.086	.114
	ClimOSM	.013	.000	.049	.787	-.085	.105
2	(Constant)	3.343	-.006	.228	.001	2.886	3.818
	Gender	-.053	-.002	.043	.229	-.138	.028
	Nat1SA	-.105	.001	.050	.025	-.202	-.013
	Lan1Eng	.007	-.002	.047	.866	-.089	.097
	Lan3OtherSA	-.052	-.001	.093	.555	-.258	.106
	Children	.000	-.001	.018	.995	-.035	.034
	Field2	.038	.002	.053	.492	-.069	.139
	Field3	-.018	.001	.056	.747	-.127	.097
	Years	-.003	.000	.002	.087	-.007	.000
	ClimIPM	.013	.002	.054	.807	-.085	.116
	ClimOSM	.013	-4.643E-5	.049	.788	-.086	.107
	MotSE	-.002	.000	.022	.927	-.044	.045

a. Unless otherwise noted, bootstrap results are based on 10000 bootstrap samples.

9.2.11. Hypothesis A4.1: OSM is significantly associated with technological propensity (AR Sample)

9.2.11.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.217	.020		60.777	.000					
	Gender	-.017	.014	-.062	-1.213	.226	-.064	-.059	-.058	.873	1.145
	Nat1SA	-.033	.015	-.108	-2.188	.029	-.104	-.106	-.105	.951	1.051
	Lan1Eng	.003	.014	.010	.197	.844	.001	.010	.009	.851	1.175
	Lan3OtherSA	-.017	.029	-.033	-.597	.551	-.029	-.029	-.029	.773	1.294
	Children	.000	.006	.002	.033	.974	-.008	.002	.002	.873	1.146
	Field2	.010	.017	.033	.601	.548	.022	.029	.029	.747	1.339
	Field3	-.008	.016	-.028	-.535	.593	-.037	-.026	-.026	.828	1.207
	Years	-.001	.001	-.088	-1.697	.090	-.078	-.082	-.081	.849	1.177
2	(Constant)	1.206	.039		31.070	.000					
	Gender	-.017	.014	-.062	-1.205	.229	-.064	-.059	-.058	.873	1.145
	Nat1SA	-.033	.015	-.109	-2.200	.028	-.104	-.106	-.106	.949	1.054
	Lan1Eng	.003	.014	.011	.210	.834	.001	.010	.010	.850	1.177
	Lan3OtherSA	-.016	.030	-.031	-.556	.579	-.029	-.027	-.027	.763	1.310
	Children	7.334E-5	.006	.001	.013	.990	-.008	.001	.001	.870	1.150
	Field2	.011	.017	.035	.634	.527	.022	.031	.030	.737	1.356
	Field3	-.008	.016	-.027	-.504	.615	-.037	-.025	-.024	.822	1.216
	Years	-.001	.001	-.089	-1.705	.089	-.078	-.083	-.082	.849	1.178
	ClimOSM	.004	.013	.016	.325	.745	.013	.016	.016	.968	1.033

a Dependent Variable: Technological propensity

9.2.11.2. Bootstrap coefficients

Bootstrap for Coefficients							
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	1.217	.000	.019	.001	1.179	1.254
	Gender	-.017	.000	.014	.232	-.044	.012
	Nat1SA	-.033	-.001	.014	.028	-.059	-.006
	Lan1Eng	.003	.000	.014	.843	-.026	.031
	Lan3OtherSA	-.017	.002	.030	.535	-.080	.037
	Children	.000	.000	.006	.974	-.011	.011
	Field2	.010	-2.232E-5	.017	.546	-.023	.042
	Field3	-.008	.000	.017	.624	-.040	.024
	Years	-.001	2.000E-5	.001	.089	-.002	.000
2	(Constant)	1.206	.002	.038	.001	1.133	1.282
	Gender	-.017	.000	.014	.236	-.044	.013
	Nat1SA	-.033	-.001	.015	.028	-.061	-.005
	Lan1Eng	.003	.000	.014	.838	-.026	.031
	Lan3OtherSA	-.016	.002	.029	.565	-.079	.038
	Children	7.334E-5	.000	.006	.988	-.011	.011
	Field2	.011	.000	.017	.532	-.023	.044
	Field3	-.008	.000	.017	.666	-.040	.026
	Years	-.001	1.900E-5	.001	.087	-.002	.000
	ClimOSM	.004	-.001	.013	.741	-.023	.030

a. Unless otherwise noted, bootstrap results are based on 10000 bootstrap samples.

9.2.12. Hypothesis A4.2. IPM is significantly associated with technological propensity (AR Sample)

9.2.12.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.218	.020		60.769	.000					
	Gender	-.016	.014	-.058	-1.130	.259	-.060	-.055	-.054	.872	1.147
	Nat1SA	-.031	.015	-.103	-2.097	.037	-.100	-.101	-.101	.951	1.051
	Lan1Eng	.001	.014	.003	.058	.954	-.005	.003	.003	.852	1.173
	Lan3OtherSA	-.020	.029	-.036	-.665	.506	-.030	-.032	-.032	.774	1.292
	Children	.000	.006	.002	.034	.973	-.008	.002	.002	.872	1.146
	Field2	.008	.017	.027	.489	.625	.019	.024	.023	.746	1.341
	Field3	-.010	.016	-.032	-.606	.545	-.039	-.029	-.029	.828	1.207
	Years	-.001	.001	-.086	-1.650	.100	-.076	-.080	-.079	.850	1.177
2	(Constant)	1.217	.038		31.821	.000					
	Gender	-.016	.014	-.058	-1.128	.260	-.060	-.055	-.054	.871	1.148
	Nat1SA	-.031	.015	-.103	-2.095	.037	-.100	-.101	-.101	.951	1.051
	Lan1Eng	.001	.015	.003	.056	.955	-.005	.003	.003	.840	1.191
	Lan3OtherSA	-.020	.030	-.036	-.661	.509	-.030	-.032	-.032	.764	1.309
	Children	.000	.006	.002	.034	.973	-.008	.002	.002	.872	1.146
	Field2	.008	.017	.027	.487	.626	.019	.024	.023	.745	1.343
	Field3	-.010	.016	-.032	-.605	.545	-.039	-.029	-.029	.828	1.208
	Years	-.001	.001	-.086	-1.646	.101	-.076	-.080	-.079	.848	1.180
	ClimIPM	.000	.013	.000	.008	.993	-.003	.000	.000	.974	1.027

a Dependent Variable: Technological propensity

9.2.12.2. Bootstrap coefficients

Bootstrap for Coefficients							
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	1.218	-.002	.020	.001	1.180	1.255
	Gender	-.016	.000	.014	.272	-.042	.013
	Nat1SA	-.031	.001	.015	.038	-.059	.001
	Lan1Eng	.001	.000	.014	.958	-.027	.029
	Lan3OtherSA	-.020	.000	.031	.526	-.080	.041
	Children	.000	9.870E-5	.006	.972	-.012	.011
	Field2	.008	.000	.015	.621	-.024	.036
	Field3	-.010	.001	.016	.571	-.039	.024
	Years	-.001	9.456E-6	.001	.104	-.002	.000
2	(Constant)	1.217	.000	.040	.001	1.138	1.298
	Gender	-.016	.000	.014	.268	-.042	.012
	Nat1SA	-.031	.001	.015	.037	-.059	.001
	Lan1Eng	.001	.000	.014	.954	-.027	.030
	Lan3OtherSA	-.020	.000	.031	.517	-.081	.042
	Children	.000	9.365E-5	.006	.971	-.011	.011
	Field2	.008	.000	.015	.612	-.024	.035
	Field3	-.010	.001	.016	.574	-.039	.024
	Years	-.001	8.904E-6	.001	.102	-.002	.000
	ClimIPM	.000	.000	.015	.991	-.029	.028

a. Unless otherwise noted, bootstrap results are based on 10000 bootstrap samples.

9.2.13. Hypothesis A5. HCI are significantly associated with productivity (AR Sample)

9.2.13.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.257	.547		2.300	.022					
	Gender	.388	.119	.168	3.271	.001	.211	.168	.161	.910	1.099
	Nat1SA	-.180	.131	-.070	-1.371	.171	-.110	-.071	-.067	.938	1.066
	Lan1Eng	.306	.126	.129	2.432	.015	.104	.126	.119	.860	1.163
	Lan3OtherSA	-.162	.291	-.031	-.555	.579	-.077	-.029	-.027	.781	1.280
	Children	.023	.050	.024	.455	.649	-.009	.024	.022	.880	1.136
	Field2	.133	.141	.054	.941	.347	.187	.049	.046	.744	1.345
	Field3	-.398	.139	-.157	-2.864	.004	-.204	-.148	-.141	.803	1.246
	ClimIPM	-.220	.130	-.090	-1.690	.092	-.031	-.088	-.083	.845	1.183
	ClimOSM	-.245	.128	-.104	-1.919	.056	-.081	-.100	-.094	.828	1.208
2	(Constant)	1.020	.539		1.891	.059					
	Gender	.254	.121	.110	2.099	.037	.211	.109	.101	.839	1.192
	Nat1SA	-.145	.129	-.056	-1.122	.263	-.110	-.058	-.054	.934	1.071
	Lan1Eng	.237	.124	.100	1.903	.058	.104	.099	.092	.843	1.187
	Lan3OtherSA	-.138	.286	-.026	-.484	.629	-.077	-.025	-.023	.781	1.281
	Children	.027	.049	.029	.559	.577	-.009	.029	.027	.880	1.137
	Field2	.050	.140	.020	.359	.720	.187	.019	.017	.727	1.375
	Field3	-.409	.136	-.161	-3.002	.003	-.204	-.155	-.145	.802	1.246
	ClimIPM	-.191	.128	-.078	-1.488	.137	-.031	-.077	-.072	.843	1.187
	ClimOSM	-.277	.126	-.117	-2.204	.028	-.081	-.114	-.106	.825	1.212
	Years	.021	.005	.208	3.963	.000	.280	.203	.191	.841	1.189

a Dependent Variable: Productivity

9.2.13.2. Bootstrap coefficients

Bootstrap for Coefficients							
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	1.257	.005	.547	.020	.191	2.397
	Gender	.388	-.003	.122	.002	.143	.629
	Nat1SA	-.180	-.010	.131	.171	-.458	.060
	Lan1Eng	.306	-.003	.127	.019	.047	.560
	Lan3OtherSA	-.162	-.004	.287	.576	-.693	.420
	Children	.023	.005	.051	.644	-.070	.134
	Field2	.133	-.007	.149	.384	-.178	.404
	Field3	-.398	-.009	.137	.006	-.682	-.133
	ClimIPM	-.220	-.002	.138	.109	-.502	.056
	ClimOSM	-.245	.003	.127	.044	-.486	.004
2	(Constant)	1.020	.001	.525	.048	-.031	2.083
	Gender	.254	-.005	.121	.038	.005	.481
	Nat1SA	-.145	-.009	.130	.268	-.416	.098
	Lan1Eng	.237	-.004	.126	.062	-.013	.487
	Lan3OtherSA	-.138	-.001	.292	.642	-.691	.449
	Children	.027	.004	.049	.566	-.063	.137
	Field2	.050	-.007	.150	.736	-.259	.336
	Field3	-.409	-.009	.136	.006	-.690	-.146
	ClimIPM	-.191	-.002	.134	.160	-.468	.075
	ClimOSM	-.277	.004	.126	.024	-.516	-.035
	Years	.021	.000	.005	.001	.011	.031

a. Unless otherwise noted, bootstrap results are based on 10000 bootstrap samples.

Crowd Worker Sample Analysis

The following abbreviations are used in the tables generated during the CW analysis, as follows.

Productivity	Crowd-worker productivity
Years	Number of years of MTurk experience
Gender	1 = male
Nationality1	1 = USA (American)
Nationality2	1 = Indian
Nationality3	1 = Foreign
Language1	1 = English
Language2	1 = Tamil
Language3	1 = Foreign language
Marital status	1 = married
Children	Number of dependent children
Profession	1 = STEM-related profession
Edu	1 = Primary School, 2 = High School, 3 = Undergraduate/Honours, 4 = Masters, 5 = PhD

9.2.14. Hypothesis A1: technological propensity is significantly associated with productivity (CW Sample)

9.2.14.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	6.466	.584		11.062	.000					
	Age	.027	.009	.147	3.192	.002	.154	.142	.140	.913	1.095
	Gender	-.089	.192	-.021	-.463	.644	-.039	-.021	-.020	.946	1.057
	Nat1USA	-.092	.271	-.022	-.341	.733	.042	-.015	-.015	.463	2.161
	Nat3Other	-.881	.358	-.118	-2.461	.014	-.104	-.110	-.108	.847	1.181
	Lan1Eng	-.246	.286	-.051	-.861	.389	.013	-.039	-.038	.542	1.845
	Children	-.132	.092	-.065	-1.445	.149	-.047	-.065	-.064	.966	1.035
	Profession	-.305	.215	-.065	-1.417	.157	-.083	-.064	-.062	.908	1.101
	Edu	.110	.135	.037	.815	.415	.037	.037	.036	.937	1.067
2	(Constant)	6.422	1.123		5.720	.000					
	Age	.027	.009	.147	3.154	.002	.154	.141	.139	.889	1.124
	Gender	-.089	.192	-.021	-.463	.643	-.039	-.021	-.020	.946	1.058
	Nat1USA	-.089	.280	-.021	-.319	.750	.042	-.014	-.014	.435	2.301
	Nat3Other	-.880	.360	-.117	-2.440	.015	-.104	-.109	-.107	.838	1.194
	Lan1Eng	-.247	.287	-.052	-.861	.390	.013	-.039	-.038	.538	1.858
	Children	-.133	.092	-.065	-1.444	.149	-.047	-.065	-.064	.964	1.038
	Profession	-.304	.215	-.065	-1.413	.158	-.083	-.064	-.062	.907	1.103
	Edu	.109	.135	.037	.807	.420	.037	.036	.036	.930	1.076
	Technological propensity	.013	.295	.002	.046	.964	-.022	.002	.002	.859	1.164

a Dependent Variable: Productivity

9.2.14.2. Bootstrap coefficients

Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	6.466	.018	.580	.001	5.314	7.621
	Age	.027	.000	.007	.001	.013	.042
	Gender	-.089	.001	.197	.640	-.478	.294
	Nat1USA	-.092	.011	.293	.739	-.659	.525
	Nat3Other	-.881	-.014	.333	.007	-1.552	-.256
	Lan1Eng	-.246	-.022	.322	.433	-.933	.337
	Children	-.132	.000	.084	.122	-.313	.027
	Profession	-.305	-.007	.230	.195	-.740	.147
	Edu	.110	-.006	.130	.384	-.160	.363
2	(Constant)	6.422	.004	1.037	.001	4.259	8.315
	Age	.027	.000	.008	.002	.013	.043
	Gender	-.089	.000	.197	.634	-.483	.292
	Nat1USA	-.089	.013	.308	.764	-.690	.533
	Nat3Other	-.880	-.013	.337	.007	-1.575	-.259
	Lan1Eng	-.247	-.023	.325	.429	-.933	.354
	Children	-.133	.000	.085	.126	-.314	.025
	Profession	-.304	-.008	.231	.196	-.752	.154
	Edu	.109	-.006	.130	.382	-.165	.361
	Technological propensity	.013	.005	.242	.958	-.421	.526

a. Unless otherwise noted, bootstrap results are based on 10000 bootstrap samples.

9.2.15. Hypothesis B1: HCI are significantly associated with productivity (CW Sample)

9.2.15.1. Coefficients and collinearity diagnostics

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	6.817	.389		17.545	.000					
	Age	.028	.008	.150	3.265	.001	.154	.145	.144	.919	1.088
	Gender	-.096	.191	-.023	-.500	.618	-.039	-.022	-.022	.948	1.055
	Nat1USA	-.143	.264	-.034	-.543	.588	.042	-.024	-.024	.489	2.047
	Nat3Other	-.892	.358	-.119	-2.494	.013	-.104	-.111	-.110	.848	1.179
	Lan1Eng	-.220	.284	-.046	-.774	.439	.013	-.035	-.034	.549	1.822
	Children	-.130	.091	-.063	-1.418	.157	-.047	-.064	-.062	.968	1.033
	Profession	-.301	.215	-.065	-1.400	.162	-.083	-.063	-.062	.909	1.101
2	(Constant)	6.466	.581		11.136	.000					
	Age	.027	.009	.147	3.192	.002	.154	.142	.140	.913	1.095
	Gender	-.089	.192	-.021	-.463	.644	-.039	-.021	-.020	.946	1.057
	Nat1USA	-.092	.271	-.022	-.341	.733	.042	-.015	-.015	.463	2.161
	Nat3Other	-.881	.358	-.118	-2.461	.014	-.104	-.110	-.108	.847	1.181
	Lan1Eng	-.246	.286	-.051	-.861	.389	.013	-.039	-.038	.542	1.845
	Children	-.132	.092	-.065	-1.445	.149	-.047	-.065	-.064	.966	1.035
	Profession	-.305	.215	-.065	-1.417	.157	-.083	-.064	-.062	.908	1.101
	Edu	.110	.135	.037	.815	.415	.037	.037	.036	.937	1.067

a Dependent Variable: TCSP

9.2.15.2. Bootstrap coefficients

Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	95% Confidence Interval	
						Lower	Upper
1	(Constant)	6.817	-.002	.414	.001	6.037	7.596
	Age	.028	8.997E-6	.007	.001	.014	.042
	Gender	-.096	.004	.196	.664	-.477	.276
	Nat1USA	-.143	-.012	.291	.647	-.682	.450
	Nat3Other	-.892	-.005	.332	.005	-1.528	-.255
	Lan1Eng	-.220	.006	.329	.508	-.843	.427
	Children	-.130	-.002	.091	.148	-.314	.050
	Profession	-.301	-.002	.229	.193	-.747	.143
2	(Constant)	6.466	.010	.592	.001	5.303	7.675
	Age	.027	4.761E-5	.007	.001	.013	.042
	Gender	-.089	.003	.196	.695	-.461	.292
	Nat1USA	-.092	-.014	.301	.766	-.650	.529
	Nat3Other	-.881	-.007	.331	.005	-1.511	-.241
	Lan1Eng	-.246	.007	.330	.453	-.888	.402
	Children	-.132	-.001	.091	.141	-.319	.048
	Profession	-.305	-.002	.230	.185	-.761	.144
	Edu	.110	-.004	.133	.401	-.165	.369

a Dependent Variable: Technological propensity

9.3. Qualitative Interview Schedule and Documents

9.3.1. Consent Forms

9.3.1.1. Consent Form for Participation

I, on this date __/__/____, state that I voluntarily choose to participate in this study. I understand that participation is my choice. I do so knowing that my identity will be protected, and my name is not to be part of the information I give. I understand that this form will be kept separate from the information collected.

Respondent's signature: _____

Researcher's signature: _____

9.3.1.2. Consent Form for Audio Recording

I, on this date __/__/____, state that I voluntarily choose to participate in this study. I understand that participation is my choice. I do so knowing that my identity will be protected, and my name is not to be part of the information I give. I understand that this form will be kept separate from the information collected.

I hereby consent to the recording of this interview.

Respondent's signature: _____

Researcher's signature: _____

9.3.2. Cover Letter

University of the Witwatersrand School of Economic and Business Sciences



Dear _____,

I am currently registered for the degree of Doctor of Philosophy, which I am completing by thesis in the Division of Human Resource Management and Management, School of Economic and Business Sciences.

I would like to invite you to take part in this research. My study is investigating the relationship between new technologies and methodologies and research productivity in the context of academic research. Participation would comprise of a 30-45-minute interview, in the form of a telephonic or video-conference (e.g. Skype) conservation and which will consist of a series of open-ended questions. Your answers, should you agree to participate would be recorded and thereafter transcribed. It is important to note that the participation is strictly voluntary, confidential and anonymous and you may withdraw at any stage, if you so wish.

The research will attempt to contribute to an improved understanding of some of the mechanisms that proliferate breakthrough innovations in academic research.

The study is for academic publication purposes only. The results of the study will be reported in my thesis, which will be published by the University of the Witwatersrand. Confidentiality is ensured at all times, and details that might specifically identify an individual are not required at any stage. Audio files and transcribed interviews will be stored on my own password protected hard-drive for further analysis and will thereafter be destroyed after a period of five

years. I undertake to conduct myself and my research in a manner that reflects the professional ethics of the university.

Any queries regarding the questionnaire or any other aspect of the study can be directed to myself or to my supervisor, Professor Chris Callaghan, on the email addresses or telephone numbers listed below.

Yours sincerely,

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(076) 626 6244

Prof. Chris Callaghan
chris.callaghan@wits.ac.za
(011) 717 8066

9.3.3. Qualitative Instrument (Interview Schedule)

University of the Witwatersrand
School of Economic and Business Sciences



Interview Schedule

Pre-Interview Determinants
Gender:
Field of Study:
Major Achievement/Breakthrough:

Introduction (Brief Background)

Interviewer: Thank you for agreeing to take the time to be interviewed. Before we begin, let me give you some context as to the study at hand. The objective of this research is to investigate scientific innovation from the perspective of *management*, to understand the determinants and combination of factors that lead to research 'breakthroughs', or those innovations that creates new knowledge, or new understanding in a given field of inquiry and to ultimately construct a typology of high performance innovative research practices. From the management perspective, the objective would be to generate innovation as efficiently as possible and furthermore, to accelerate the rate at which innovation occurs (this is often seen as counter-intuitive to scientific research). These questions are designed to understand what contributed to your research breakthroughs and your thoughts on how future research breakthroughs could be attained.

Introductory Questions (±10 minutes)

1. Please briefly describe your area(s) of research and your biggest research breakthrough/achievement in your career? Also, please list – in order of importance – the most important influences that enabled this breakthrough?

2. Was there anything specific in your background – experience, education, training - that contributed to your breakthrough work? How do you think your prior experience contributed to your (biggest/major) breakthrough?

3. How do you think your prior education and training contributed to your biggest research breakthrough?

4. **Probing question**: Were there any other factors that you think contributed to your research breakthrough? (training, internal/external support, collaboration, etc.)?

Question 1 (±5 minutes)

Do you feel that journal publications that accept academic work in your field sufficiently promote innovative research in your field? Did you experience any type of resistance from the academic publishing system when trying to publish your breakthrough?

Question 2 (±10 minutes)

Hypothetically, if you were an HR/hiring manager, looking for researchers who are able to produce research breakthroughs – what characteristics would you look for?

Probing Question 2.1:

In your experience, which personality factors do you think contribute to attaining a research breakthrough? (± 5 minutes)

Probing Question 2.2:

In your experience what motivational values do you think contribute to attaining a research breakthrough? (±5 minutes)

Probing Question 2.3:

In your experience what are the characteristics of a work climate that is conducive to attaining a research breakthrough? (±5 minutes)

Questions 3 (±5 minutes)

The 'management' of scientific research is sometimes considered counter-productive. Do you think it is necessary, or even possible to try to enhance the effectiveness/efficiency of scientific research, or to try accelerate the rate at which breakthrough innovations occur? And why/why not?

Question 3: (±5 minutes)

In our increasingly globalized world we often find that what once may have been smaller, localised problems have begun to spread on a more global basis. A prime example was the Ebola outbreak of 2014 which quickly became a worldwide phenomenon. What is science and scientists and researchers' role in addressing these kind of global problems, what is the best way for scientists around the world to address these kind of problems, which seem to occur almost in real-time?

Probing Question 3.1:

There's been a recent trend in the use of open innovation – obtaining data from large numbers of people spread across different geographical locations through the Internet and social media and smart technology. This has become very popular in health/medical research; known as participative science. What are your thoughts on using these types of technologies to gather data in your field?

Probing Question 5: (±5 minutes)

A lot of research face budget constraints. Can you think of any way to streamline research funding or think of alternate methods of research funding?

Final Thoughts

Are there any final thoughts you would like to share?

Thank you for your participation.

8.4. The Quantitative Questionnaire and Documents

8.4.1. Consent Forms

8.4.1.1. Consent Form for Participation

I, on this date __/__/____, state that I voluntarily choose to participate in this study. I understand that participation is my choice. I do so knowing that my identity will be protected, and my name is not to be part of the information I give. I understand that this form will be kept separate from the information collected.

Respondent's signature: _____

Researcher's signature: _____

9.4.3. Cover Letter

University of the Witwatersrand School of Economic and Business Sciences



Dear _____,

I am currently registered for the degree of Doctor of Philosophy, which I am completing by thesis in the Division of Human Resource Management and Management, School of Economic and Business Sciences.

I would like to invite you to take part in this research. My study is investigating the relationship between new technologies and methodologies and research productivity in the context of academic research. Participation would comprise of completing a 10-15-minute online survey. This survey is both confidential and anonymous. Your participation is completely voluntary and involves no risk, penalty, or loss of benefits whether or not you participate. You may withdraw from the survey at any stage.

The research will attempt to contribute to an improved understanding of some of the mechanisms that proliferate breakthrough innovations in academic research.

The study is for academic publication purposes only. The results of the study will be reported in my thesis, which will be published by the University of the Witwatersrand. Confidentiality is ensured at all times, and details that might specifically identify an individual are not required at any stage. Completed questionnaires will be stored on my own password protected hard-

drive for further analysis and will thereafter be destroyed after a period of five years. I undertake to conduct myself and my research in a manner that reflects the professional ethics of the university.

You can access the questionnaire by clicking on this link:

https://www.surveymonkey.com/r/PLXK6DC

Any queries regarding the questionnaire or any other aspect of the study can be directed to myself or to my supervisor, Professor Chris Callaghan, on the email addresses or telephone numbers listed below.

Yours sincerely,

Asaf Rubin
rubinsav@gmail.com
(076) 626 6244

Prof. Chris Callaghan
chris.callaghan@wits.ac.za
(011) 717 8066

9.4.4. Questionnaires

Questionnaires were hosted on SurveyMonkey. The layout of the online, SurveyMonkey version of these questionnaires differs from the layout presented here.

9.4.4.1. Academic Research Questionnaire

Section A

The following are several questions about you, your background, and the place where you work. These questions are important because they help us to see if different types of people respond to the questions on the questionnaire in different ways. They are NOT used to identify any individual.

1. What is your age? [Text box]

2. What is your gender?
   - Male []
   - Female []
   - Prefer not to say []

3. What country were you born in? [Text box]

4. What is your first language? [Text box]

5. How many years of experience do you have as a researcher? [Text box]

6. How many dependent children do you support in your family? [Text box]

7. In what field do you primarily research? [Text box]

8. How many ISIS/IBBS/Norwegian List/Scopus (internationally accredited) journal articles (in total) have you had published (including those accepted for publication)? [Text box]

9. How many DOHET (locally accredited journal articles (in total) have you had published (including those accepted for publication)?

10. What is your title?
    - Mr./Mrs./Ms. []
    - Dr. []
    - Associate/Adjunct Prof. []
    - Prof. []

11. Are you married?
    - Yes []
    - No []

Section B

Here are a number of characteristics that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

I see myself as...

1. Disagree Strongly
2. Disagree moderately
3. Disagree a little

4. Neither agree nor disagree
5. Agree a little
6. Agree moderately
7. Strongly agree

1. Extraverted, enthusiastic
2. Critical, quarrelsome
3. Dependable, self-disciplined
4. Anxious, easily upset
5. Open to new experiences, complex
6. Reserved, quiet
7. Sympathetic, warm
8. Disorganized, careless
9. Calm, emotionally stable
10. Conventional, uncreative
11. Outgoing, talkative
12. Untrusting, suspicious
13. Efficient, organized
14. Tense, worrying
15. Curious, imaginative
16. Introverted, shy
17. Forgiving, generous
18. Extravagant, self-indulgent
19. Confident, self-assured
20. Conservative, orthodox
21. Active, assertive
22. Appreciative, thankful
23. Reliable, responsible
24. Self-conscious, vulnerable
25. Artistic, creative

Section C.1 (male respondents)

Here we briefly describe some people. Please read each description and think about how much each person is or is not like you. Tick the box to the right that shows how much the person in the description is like you. How much is this person like you?
Note: Section C.1 for males, C.2 for females (pronouns changed).

1. Very much like me
2. Like me
3. Somewhat like me
4. A little like me
5. Not like me
6. Not at all like me

1. Thinking up new ideas and being creative is important to him. He likes to do things in his own original way.
2. It is important to him to be rich. He wants to have a lot of money and expensive things.
3. He thinks it is important that every person in the world should be treated equally. He believes everyone should have equal opportunities in life.
4. It's important to him to show his abilities. He wants people to admire what he does.
5. It is important to him to live in secure surroundings. He avoids anything that might endanger his safety.
6. He likes surprises and is always looking for new things to do. He thinks it is important to do lots of different things in life.

7. He believes that people should do what they are told. He thinks people should follow rules at all times, even when no-one is watching.

8. It is important to him to listen to people who are different from him. Even when he disagrees with them, he still wants to understand them.

9. It is important to him to be humble and modest. He tries not to draw attention to himself.

10. Having a good time is important to him. He likes to "spoil" himself.

11. It is important to him to make his own decisions about what he does. He likes to be free and not depend on others.

12. It's very important to him to help the people around him. He wants to care for their well-being.

13. Being very successful is important to him. He hopes people will recognise his achievements.

14. It is important to him that the government ensures his safety against all threats. He wants the state to be strong so it can defend its citizens.

15. He looks for adventures and likes to take risks. He wants to have an exciting life.

16. It is important to him always to behave properly. He wants to avoid doing anything people would say is wrong.

17. It is important to him to get respect from others. He wants people to do what he says.

18. It is important to him to be loyal to his friends. He wants to devote himself to people close to him.

19. He strongly believes that people should care for nature. Looking after the environment is important to him.

20. Tradition is important to him. He tries to follow the customs handed down by his religion or his family.

21. He seeks every chance he can to have fun. It is important to him to do things that give him pleasure.

Section C.2. (female respondents)

1. Thinking up new ideas and being creative is important to her. She likes to do things in her own original way.

2. It is important to her to be rich. She wants to have a lot of money and expensive things.

3. She thinks it is important that every person in the world should be treated equally. She believes everyone should have equal opportunities in life.

4. It's important to her to show her abilities. She wants people to admire what she does.

5. It is important to her to live in secure surroundings. She avoids anything that might endanger her safety.

6. She likes surprises and is always looking for new things to do. She thinks it is important to do lots of different things in life.

7. She believes that people should do what they are told. She thinks people should follow rules at all times, even when no-one is watching.

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16. It is important to her always to behave properly. She wants to avoid doing anything people would say is wrong.

17. It is important to her to get respect from others. She wants people to do what she says.

18. It is important to her to be loyal to her friends. She wants to devote herself to people close to her.

19. She strongly believes that people should care for nature. Looking after the environment is important to her.

20. Tradition is important to her. She tries to follow the customs handed down by her religion or his family.

21. She seeks every chance she can to have fun. It is important to her to do things that give her pleasure.

Section D

Here are some statements about the university where you work, that may or may not apply to you. To what extent do you agree or disagree with these statements? Please mark you answers in the appropriate column.

1. Definitely false
2. Mostly False
3. Mostly True
4. Definitely true

1. In this university, the way people work together is readily changed in order to improve performance
2. The methods used by this university to get the job done are often discussed
3. Changes in the way things are done here happen very slowly
4. Nobody gets too upset if people break the rules around here
5. This university is very flexible; it can quickly change procedures to meet new conditions and solve problems as they arise
6. Management here are quick to spot the need to do things differently
7. Everything has to be done by the book
8. Assistance in developing new ideas is readily available
9. New ideas are readily accepted here
10. It is considered extremely important here to follow the rules

11. This university is quite inward looking; it does not concern itself with what is happening in in the international education and research sphere
12. There are regular discussions as to whether people in the university are working effectively together
13. This university is quick to respond when changes need to be made
14. People in this university are always searching for new ways of looking at problems
15. Ways of improving help to students are not given much thought
16. Student needs are not considered top priority here
17. The way this university does things has never changed very much
18. It's not necessary to follow procedures to the letter around here
19. In this university, time is taken to review long-term university objectives
20. People can ignore formal procedures and rules if it helps get the job done
21. Management are not interested in trying out new ideas
22. In this university, objectives are modified in light of changing circumstances
23. Senior management like to keep to established, traditional ways of doing things
24. This university is slow to respond to the needs of the students
25. This university is continually looking for new opportunities to enhance its research output

Section E

To what extent do you agree/disagree with the following statements?

1. Strongly Disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly Agree

1. I think it is important that journal publications exercise extreme caution in the publication of research that does not strictly adhere to broadly accepted research methodologies and paradigms.

2. Wikipedia is a useless tool for academic research
3. I am happy with my current method of obtaining research funding.
4. My research would benefit from perspectives from people from different fields of expertise – both academic and non-academic
5. I don't typically collaborate on my research projects; I prefer to work alone
6. The emergence of certain new technological advancements has made me look at my research from a new perspective
7. These days it feels like there's a constant 'information overload' because of the Internet and how easily information is shared
8. I would use crowd-funding (obtaining funds from a large undefined network of people to reach a monetary goal online, e.g. KickStarter) to obtain research funds
9. I generally stick to my own area of expertise – I'm not knowledgeable enough to research in other fields
10. I try to get feedback on my research from non-academics.
11. I do not often pursue research projects that are high risk
12. I am always up to date with the latest technological advances like new software, applications, social networks and gadgets.
13. Solving serious research problems is best left to the professionals and academics
14. Problem solving doesn't require creative thinking – it requires hard facts and figures. (Reversed)
15. I only collaborate with researchers from my own research discipline
16. I am motivated by the fact that my research may hold the potential to introduce important change to the world
17. When I get sick, the first thing I do is look up my symptoms on the internet.
18. I would use online social media to collect research data (e.g. Twitter, Facebook, Instagram, etc.)
19. I have used (or would use) Linux or other forms of open source software for my research
20. I often collaborate with researchers from other disciplines on research projects.

Section F

Please answer the following questions

1. Yes
2. No

1. Would you smile at people every time you meet them?
2. Do you always practice what you preach?
3. If you say to people that you will do something, do you always keep your promise, no matter how inconvenient it may be?
4. Would you ever lie to people?

~END~

Thank you for participating in this study. Your contribution is appreciated and is invaluable to the research.

9.4.3.2. Crowd-Worker Questionnaire

Section A

The following are several questions about you, your background, and the place where you work. These questions are important because they help us to see if different types of people respond to the questions on the questionnaire in different ways. They are NOT used to identify any individual.

1. What is your age? [Text box]

2. What is your gender?
   - Male []
   - Female []
   - Prefer not to say []

3. What country were you born in? [Text box]

4. What is your first language? [Text box]

5. How many dependent children do you support in your family? [Text box]

6. What is your profession? [Text box]

7. Which industry do you work in? [Text box]

8. How many MTurk projects (in total) have you completed? [Text box]

9. How many years (in total) have you been working on MTurk? [Text box]

10. What level of education have you received?
    - Primary (0-7 years) []
    - High School (8-12 years) []
    - Undergraduate/Honours (13-16 years) []
    - Masters (17-18 years). []
    - PhD (19+ years) []

11. Are you married?
    - Yes []
    - No []

Section B

Here are a number of characteristics that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

I see myself as...

1. Disagree Strongly
2. Disagree moderately
3. Disagree a little
4. Neither agree nor disagree

5. Agree a little
6. Agree moderately
7. Strongly agree

1. Extraverted, enthusiastic
2. Critical, quarrelsome
3. Dependable, self-disciplined
4. Anxious, easily upset
5. Open to new experiences, complex
6. Reserved, quiet
7. Sympathetic, warm
8. Disorganized, careless
9. Calm, emotionally stable
10. Conventional, uncreative
11. Outgoing, talkative
12. Untrusting, suspicious
13. Efficient, organized
14. Tense, worrying
15. Curious, imaginative
16. Introverted, shy
17. Forgiving, generous
18. Extravagant, self-indulgent
19. Confident, self-assured
20. Conservative, orthodox
21. Active, assertive
22. Appreciative, thankful
23. Reliable, responsible
24. Self-conscious, vulnerable
25. Artistic, creative

Section C.1 (male respondents)

Here we briefly describe some people. Please read each description and think about how much each person is or is not like you. Tick the box to the right that shows how much the person in the description is like you. How much is this person like you?
Note: Section C.1 for males, C.2 for females (pronouns changed).

1. Very much like me
2. Like me
3. Somewhat like me
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6. Not at all like me

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2. It is important to him to be rich. He wants to have a lot of money and expensive things.
3. He thinks it is important that every person in the world should be treated equally. He believes everyone should have equal opportunities in life.
4. It's important to him to show his abilities. He wants people to admire what he does.
5. It is important to him to live in secure surroundings. He avoids anything that might endanger his safety.
6. He likes surprises and is always looking for new things to do. He thinks it is important to do lots of different things in life.
7. He believes that people should do what they are told. He thinks people should follow rules at all times, even when no-one is watching.
8. It is important to him to listen to people who are different from him. Even when he disagrees with them, he still wants to understand them.
9. It is important to him to be humble and modest. He tries not to draw attention to himself.
10. Having a good time is important to him. He likes to “spoil” himself.
11. It is important to him to make his own decisions about what he does. He likes to be free and not depend on others.

12. It's very important to him to help the people around him. He wants to care for their well-being.

13. Being very successful is important to him. He hopes people will recognise his achievements.

14. It is important to him that the government ensures his safety against all threats. He wants the state to be strong so it can defend its citizens.

15. He looks for adventures and likes to take risks. He wants to have an exciting life.

16. It is important to him always to behave properly. He wants to avoid doing anything people would say is wrong.

17. It is important to him to get respect from others. He wants people to do what he says.

18. It is important to him to be loyal to his friends. He wants to devote himself to people close to him.

19. He strongly believes that people should care for nature. Looking after the environment is important to him.

20. Tradition is important to him. He tries to follow the customs handed down by his religion or his family.

21. He seeks every chance he can to have fun. It is important to him to do things that give him pleasure.

Section C.2. (female respondents)

22. Thinking up new ideas and being creative is important to her. She likes to do things in her own original way.

23. It is important to her to be rich. She wants to have a lot of money and expensive things.

24. She thinks it is important that every person in the world should be treated equally. She believes everyone should have equal opportunities in life.

25. It's important to her to show her abilities. She wants people to admire what she does.

26. It is important to her to live in secure surroundings. She avoids anything that might endanger her safety.

27. She likes surprises and is always looking for new things to do. She thinks it is important to do lots of different things in life.

28. She believes that people should do what they are told. She thinks people should follow rules at all times, even when no-one is watching.

29. It is important to her to listen to people who are different from her. Even when she disagrees with them, she still wants to understand them.

30. It is important to her to be humble and modest. She tries not to draw attention to herself.

31. Having a good time is important to her. She likes to "spoil" herself.

32. It is important to her to make his own decisions about what she does. She likes to be free and not depend on others.

33. It's very important to her to help the people around her. She wants to care for their well-being.

34. Being very successful is important to her. She hopes people will recognise her achievements.

35. It is important to her that the government ensures his safety against all threats. She wants the state to be strong so it can defend its citizens.

36. She looks for adventures and likes to take risks. She wants to have an exciting life.

37. It is important to her always to behave properly. She wants to avoid doing anything people would say is wrong.

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39. It is important to her to be loyal to her friends. She wants to devote herself to people close to her.

40. She strongly believes that people should care for nature. Looking after the environment is important to her.

41. Tradition is important to her. She tries to follow the customs handed down by her religion or his family.

42. She seeks every chance she can to have fun. It is important to her to do things that give her pleasure.

Section D

To what extent do you agree/disagree with the following statements?

1. Strongly Disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly Agree

1. I'm a firm believer in the term 'rules are rules'
2. I wouldn't rely on Wikipedia if I want 100% accurate information
3. I would contribute money to a KickStarter project if I thought it was a good enough idea.
4. I think asking people's advice on social media is a great way to get a good answer.
5. I don't enjoy teamwork; I prefer to work alone.
6. New technologies have made me look at the world from a new perspective
7. These days it feels like there's a constant 'information overload' because of the Internet and how easily information is shared.
8. If I were to start a business of my own, I would use crowdfunding (e.g. KickStarter) to raise funding.
9. I stick to what I know – I wouldn't comment on something I know nothing about.
10. I try get feedback on my ideas from family and friends
11. I do not consider myself much of a risk-taker
12. I am always up to date with the latest technological advances like new software, applications, social networks and gadgets.
13. Solving serious world problems is best left to the professionals
14. Problem solving doesn't require creative thinking – it requires hard facts and figures.
15. If I have a problem, I'll usually try solve it myself before asking people for help
16. Technology is changing the world for the better
17. When I get sick, the first thing I do is look up my symptoms on the internet.

18. I would use online social media to try find a solution to a problem I have (e.g. Twitter, Facebook, Instagram, etc.)
19. I am always interested to hear other people's opinions on current events.
20. I like to work with different people from backgrounds that are different to mine

Section F

Please answer the following questions

1. Yes
2. No

1. Would you smile at people every time you meet them?
2. Do you always practice what you preach?
3. If you say to people that you will do something, do you always keep your promise, no matter how inconvenient it may be?
4. Would you ever lie to people?

~END~

Thank you for participating in this study. Your contribution is appreciated and is invaluable to the research.

9.7 University Certificates of Clearance

9.7.1. The University of Witwatersrand

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

OFFICE OF THE DEPUTY REGISTRAR

18 April 2017

Mr Asaf Rubin
PhD Candidate
School of Economic and Business Sciences

TO WHOM IT MAY CONCERN

"Knowledge Management Determinants of Breakthrough Research Productivity"

This letter serves to confirm that the above project has received permission to be conducted on University premises, and/or involving staff and/or students of the University as research participants. In undertaking this research, you agree to abide by all University regulations for conducting research on campus and to respect participants' rights to withdraw from participation at any time.

If you are conducting research on certain student cohorts, year groups or courses within specific Schools and within the teaching term, permission must be sought from Heads of School or individual academics.

Ethical clearance has been obtained.

Nicoleen Potgieter
Deputy Registrar

Private Bag 3, Wits, 2050, South Africa | T +27 11 717 1204/8 | F +27 86 553 2271 | www.wits.ac.za

9.7.2. The University of Cape Town

Faculty of Commerce
Private Bag X3, Rondebosch, 7701
2.26 Leslie Commerce Building, Upper Campus
Tel: +27 (0) 21 650 4375/ 5748 Fax: +27 (0) 21 650 4369
E-mail: com-faculty@uct.ac.za
Internet: www.uct.ac.za
@Commerce_UCT **UCT Commerce Faculty Office**

15 May 2017

Mr Asaf Rubin
School of Management Studies
University of Cape Town

Dear Mr Rubin

Project: Knowledge Management Determinants of Breakthrough Research Productivity.

Thank you for submitting your study to the Faculty of Commerce Ethics in Research Committee.

It is a pleasure to inform you that the EiRC has **formally approved** the above-mentioned study.

Approval is granted for the period of 12 months. Should you require an extension or make any substantial changes to the research methodology which could affect the experiences of participants, you must submit a revised protocol to the Committee for approval.

Please note that the ongoing ethical conduct of the study remains the responsibility of the principal investigator.

Your sincerely

Kind Regards
SAMANTHA ALEXANDER
Administrative Assistant
University of Cape Town
Commerce Faculty Office
Room 2.24 | Leslie Commerce Building

Office Telephone: +27 (0)21 650 2695
Office Fax: +27 (0)21 650 4369
E-mail: samantha.alexander@uct.ac.za
Website: www.commerce.uct.ac.za<http://www.commerce.uct.ac.za/>

9.7.3. The University of Pretoria

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Faculty of Humanities
Research Ethics Committee

8 August 2017

Dear Mr Rubin

Project:	**Knowledge management determinants of breakthrough research productivity**
Researcher:	**A Rubin**
Department:	**Department of Management (Wits University)**
Reference number:	**GW20170732HS (External research)**

Thank you for your response to the Committee's correspondence of 30 July 2017

I have pleasure in informing you that the Research Ethics Committee formally **approved** the above study at an *ad hoc* meeting held on 8 August 2017. Data collection may therefore commence.

Please note that this approval is based on the assumption that the research will be carried out along the lines laid out in the proposal. Should your actual research depart significantly from the proposed research, it will be necessary to apply for a new research approval and ethical clearance.

We wish you success with the project.

Sincerely

Prof Maxi Schoeman
Deputy Dean: Postgraduate and Research Ethics
Faculty of Humanities
UNIVERSITY OF PRETORIA
e-mail: tracey.andrew@up.ac.za

Research Ethics Committee Members: **Prof MME Schoeman (Deputy Dean);** Prof KL Harris; Dr L Blokland; Ms A dos Santos; Dr R Fasselt; Ms KT Govinder; Dr E Johnson; Dr C Panebianco; Dr C Puttergill; Dr D Reyburn; Dr M Taub; Prof GM Spies; Prof E Taljard; Ms B Tsebe; Dr E van der Klashorst; Dr G Wolmarans; Ms D Mokalapa

9.8.4. Nelson Mandela Metropolitan University

• PO Box 77000 • Nelson Mandela Metropolitan University
• Port Elizabeth • 6031 • South Africa • www.nmmu.ac.za

Nelson Mandela Metropolitan University
for tomorrow

Chairperson: Research Ethics Committee (Human)
Tel: +27 (0)41 504-2235

Ref: [H16-BES-BMA-EXT-001/Amendment]

Contact person: Mrs U Spies

20June 2017

Dr J Krüger
Faculty: Business and Economic Sciences
South Campus

Dear Dr Krüger

KNOWLEDGE MANAGEMENT DETERMINANTS OF BREAKTHROUGH RESEARCH PRODUCTIVITY

PRP: Dr J Krüger
PI: Mr A Rubin

We take pleasure in informing you that the Research Ethics Committee (Human) approved the amendments to the methodology of protocol **H16-BES-BMA-EXT-001**.

An annual affirmation to the effect that the protocols in use are still those for which approval was granted, will be required from you. You will be reminded timeously of this responsibility, and will receive the necessary documentation well in advance of any deadline.

We wish you well with the project. Please inform your co-investigators of the outcome, and convey our best wishes.

Yours sincerely

CB Cilliers

Prof CB Cilliers
Chairperson: Research Ethics Committee (Human)

cc: Department of Research Capacity Development
Faculty Officer: BES

9.7.5. The University of Kwa-Zulu Natal

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

21 April 2017

Mr Asaf Rubin
School of Economics and Business Science
University of Witwatersrand
JOHANNESBURG
Email: rubinsav@gmail.com

Dear Mr Rubin

RE: PERMISSION TO CONDUCT RESEARCH

Gatekeeper's permission is hereby granted for you to conduct research at the University of KwaZulu-Natal (UKZN), towards your postgraduate degree, provided Ethical clearance has been obtained. We note the title of your research project is:

"Knowledge management determinants of breakthrough research productivity".

It is noted that you will be constituting your sample by handing out questionnaires to Academics from UKZN.

Please ensure that the following appears on your notice/questionnaire:

- Ethical clearance number;
- Research title and details of the research, the researcher and the supervisor;
- Consent form is attached to the notice/questionnaire and to be signed by user before he/she fills in questionnaire;
- gatekeepers approval by the Registrar.

You are not authorized to contact staff and students using 'Microsoft Outlook' address book. Data collected must be treated with due confidentiality and anonymity.

Yours sincerely

MR SS MOKOENA
REGISTRAR

9.7.6. Cape Peninsula University of Technology (CPUT)

Cape Peninsula University of Technology

Office of the Deputy Vice Chancellor:
Research, Technology Innovation & Partnerships
Bellville Campus
P O Box 1906
Bellville 7535
Tel: 021-9596242
Email: NhlapoC@cput.ac.za

25 January 2018

Mr Asaf Rubin
School of Economics and Business Sciences
University of the Witwatersrand
Johannesburg

Email: rubinsav@gmail.com

Dear Mr Rubin

RE: PERMISSION TO CONDUCT RESEARCH AT CPUT

The Institutional Ethics Committee received your application entitled:"Knowledge Management Determinants of Breakthrough Research Productivity" together with the dossier of supporting documents.

Permission is herewith granted for you to do research at the Cape Peninsula University of Technology.

Wishing you the best in your study.

Sincerely

APPROVED
Chair Senate Ethics Committee
25 JAN 2018
Cape Peninsula University of Technology
Sign: .....

PO Box 1906 Bellville 7535 South Africa
086 123 2788

9.7.7. Rhodes University

RHODES UNIVERSITY
Where leaders learn

Human Resources Division
Office of the HR Director
Administration Building, Grahamstown, 6139, South Africa
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e: l.govender@ru.ac.za

www.ru.ac.za

22 August 2017

Mr A Rubin
School of Economics and Business Science
University of Witwatersrand
rubinsav@gmail.com

Dear Mr Rubin

REQUEST TO CONDUCT RESEARCH WITH RHODES UNIVERSITY STAFF AND/OR STUDENTS

This letter is to confirm that your request to conduct research on ***"The Knowledge Management Determinants of Breakthrough Research Productivity"*** topic has been approved by the Ethics Committee. In my capacity as HR Director, I do not have any objection should you wish to follow a coordinated approach by surveying and/or interviewing staff.

Should you require further information please do not hesitate to contact me.

Yours sincerely



Loshni Govender
HR Director

9.7.8. University of Fort Hare

University of Fort Hare
OFFICE OF UNIVERSITY REGISTRAR
Alice (main) Campus:
Private Bag X1314, King William's Town Road, Alice, 5700, RSA
Tel: +27 (0) 40 602 - 2501 • Fax: +27 (0) 40 602 - 2577
Email: nmabindisa@ufh.ac.za

University of Fort Hare
Together in Excellence

August 28, 2017

Mr. Asaf Rubin
29 Andre Street, Johannesburg
2195

rubinsav@gmail.com

Dear Mr. Rubin

Approval from the Registrar's Office to Conduct Research

Having consulted the Chairperson of the Research Ethics Committee, I hereby grant permission for Mr. Rubin to conduct research relating to her thesis "". Knowledge Management Determinants of Breakthrough Research Productivity"

We look forward to reading the research report.

Kind regards

Prof M Somniso
University Registrar

Bhisho Campus: P. O Box 1153, KWT 5600, Independence Avenue , Bhisho, 5600, RSA
Tel: +27 (0) 40 608 - 3407 • Fax: +27 (0) 40 608 - 3408

East London Campus: Private Bag X9083, EL 5200, 50 Church Street, East London, 5201, RSA
Tel: +27 (0) 43 704 - 7000 • Fax: +27 (0) 43 704 - 7095
V/C Dial Up: +27 (0) 43 704 - 7143/ 7144

www.ufh.ac.za

9.7.9. University of Western Cape (UWC)

UNIVERSITY of the WESTERN CAPE

STUDENT ADMINISTRATION
Administration Building, 1st Floor
ashaikjee@uwc.ac.za, nschoeman@uwc.ac.za
021 959 2110

21 August 2017

RE: PERMISSION TO CONDUCT RESEARCH AT THE UNIVERSITY OF THE WESTERN CAPE

Name of Researcher	:	Asaf Rubin
Research Topic	:	The Knowledge Management Determinants of Breakthrough Research Productivity
Date of issue	:	21/08/2017
Reference number	:	UWCRP210817AR

As per you request, we acknowledge that you have obtained the necessary permissions and ethics clearances and are welcome to conduct your research as outlined in your proposal and communication with us.

Please note that while we give permission to conduct such research (i.e. interviews and surveys) staff and students at this University are not compelled to participate and may decline to participate should they wish to.

Should you wish to make use of or reference to the University's name, spaces, identity, etc. in any publication/s, you must first furnish the University with a copy of the proposed publication/s so that the University can verify and grant permission for such publication/s to be made publicly available.

Should you require any assistance in conducting your research in regards to access to student contact information please do let us know so that we can facilitate where possible.

Yours sincerely

DR AHMED SHAIKJEE
DEPUTY REGISTRAR: ACADEMIC ADMINISTRATION
OFFICE OF THE REGISTRAR

UWCRP210817AR

FROM HOPE TO ACTION THROUGH KNOWLEDGE.