ABSTRACT

This Delphi Study's main thrust is to investigate market preference and equipment management data, i.e., big data in product development. Subsequently, testing how linking these to flexible manufacturing systems design and operations can maximise plant utilisation in the FMCG industry. In this sequential exploratory mixed methods inquiry with sixteen (16) panellists, a framework that links big data to maximised plant utilisation, through twelve (12) hypotheses is tested. The study suggests that the results are in line with extant literature on the investigated constructs and linkages. The findings strengthen extant literature and contribute empirical evidence to applying big data in the supply chain and product lifecycle management work-processes. The results confirm big data's potential to improve collaboration across the investigated value chain. The findings of this research have regulatory implications for government, strategy implications for practitioners and research implications for academia.

DEDICATION

Ngalo msebenzi ndibeka umnombo nezizukulwana ezindifikise kweli nqwanqwa…nazo zonke iintsapho ezikhubeke kwiliwa lentswela endleleni eya ekuziphuhliseni…Sizophumelela!

ACKNOWLEDGEMENTS

In my LORD and Saviour, GOD the Father, the Son and the Holy Ghost I "live, and move and have my being", for this reason, I echo: "Now unto the King eternal, immortal, invisible, the only wise God, be honour and glory for ever and ever. Amen!"

To my parents Zamekile & Goitsimang Vuyelwa: I am grateful. Thank you for your unconditional love and unwavering confidence and support of my life journey. Without you, none of this would have been! I honour you!!!

To my research supervisor, Professor Raj Siriram. Thank you for your guidance in presenting scholarly work and contributing to the growing research body of knowledge. You are exceptional, and I am honoured to have been trained by you.

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The friends who made my initial research work possible from Gqeberha (Port Elizabeth): Ms Nomsa "Gcobo" Xubane and Qinisani "Queh" Qwabe; thank you! *Liyinene elithi: "Umntu ngumntu ngabantu!" andahlukanga nganto, nindenze emntu ebantwini*: B. Sandile "Motase" Ndima, words are just not enough, *ngiyabonga*! Dr Ntsikelelo Breakfast, Ms Lungelwa Jacobs, Ms Lyn-Anne Hooper, Thabo Letlaka, Ms Zintle Letlaka, Dr Savo Heleta, Tebogo Thothela, Mbekezeli "Marty" Benjamin, Yannick Moise Ilunga, Dr Kwezikazi Molamodi, Thabang Moloi, Bathandwa Ndzulu, Nhlanhla Mdhlalose, Ms Nosipho Gumede, Ms Lungile Hlatshwayo, Lincoln Jansen, Mthuthuzeli Vongo, Ms Bertha Itana, Modisha Maribe and Ms Mso Kandanisa *uTshay' ingwe uyabulela!* To my colleagues, present and past, who supported me in various ways, thank you. My family, friends and brothers, Zingisa and Ludwe Vuyelwa THANK YOU!! *Maz' enethole! Nangamso! Nenjenjalo nakwabalandelayo!*

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CHAPTER 1: INTRODUCTION

1.1 Research Background and Motivation

Until the recent past, factories' low throughput rates, i.e. capacity constraints, have constrained manufacturers' ability to fulfil product orders (Kadwa, 2013; Thompson, Martin & Scott, 2017). Manufacturing refers to the activity of making saleable products from raw materials on a large scale through the use of tools, labour and machines (du Preez et al., 2015). The referred to capacity constraints have had an adverse impact on the overall performance of the relevant supply chain. A supply chain is defined as: "the entire network of organisations and activities involved in (1) designing a set of products or services and related processes, (2) acquiring and converting inputs into these products or services, (3) distributing and consuming these products or services, and, (4) disposing of these products or services" (Melnyk et al., 2009: 4651).

According to Hausman (2004), the performance of the supply chain refers to the extended supply chain's operational tasks to fulfil the consumer's requirements. The requirements include the availability of a product, delivery timing, and the requisite inventory and capacity in the supply chain to perform these tasks responsively (Hausman, 2004). The definitions offered by Melnyk et al. (2009) and Hausman (2004) highlight the position of manufacturing within the supply chain. Moreover, the definitions, at the very least, give a face value indication of how the performance of processes in manufacturing can have a ripple effect on the entire supply chain.

A noteworthy point in the definition of a supply chain is the referred to is seen as a process with sub-processes. These sub-processes include the design of products and the manufacture of the same in sequence, *inter alia*.

Several more instances in literature agree with this view; yet the product design sub-process is typically omitted and treated as a separate sub-process from the other sub-processes of the supply chain (Novak & Eppinger, 2001; Khan, Christopher & Creazza, 2012; Nepal, Monplaisir & Famuyiwa, 2012; Labbi, Ouzizi & Douimi, 2015; Irfan, Wang & Akhtar, 2019). Hausman's (2004) description of supply chain performance also supports this segmented approach.

In the segmented approach, product design is typically only aligned and connected to the supply chain processes considerably late in supply chain management, i.e., just before the manufacture of a product commences. By implication, the complications that arise when aligning and connecting the product design sub-processes to the rest of the supply chain sub-processes can ripple through the supply chain. These possible complications in alignment and connection present another significant factor to be considered in supply chain performance. Since, at present common practice does not connect product design to the rest of the supply chain sub-processes, the contribution of this factor can be missed. Thus, it can obscure indicators of a supply chain's performance.

The obscurity in a supply chain's performance measurement is highlighted in that product lifecycle management (PLM) is defined and treated as unrelated to the supply chain work process. The treatment of these work processes as unrelated processes persists despite a notably prominent interception in the constructs that define PLM with those of a supply chain. This intercept is evident in the definition of PLM tendered by du Preez et al. (2015). According to du Preez et al. (2015), PLM entails the process of managing a product's full lifecycle from its ideation through design and manufacture to its use and its disposal. The PLM process is cyclic with the phases in a sequence which includes: concept, definition, design, industrialisation, production, distribution, product support and disposal of the product (du Preez et al., 2015). Further, du Preez et al. (2015), drawing from Noyan's (2004) work, propose that the phases shown in Figure 1.1 may be part of PLM.

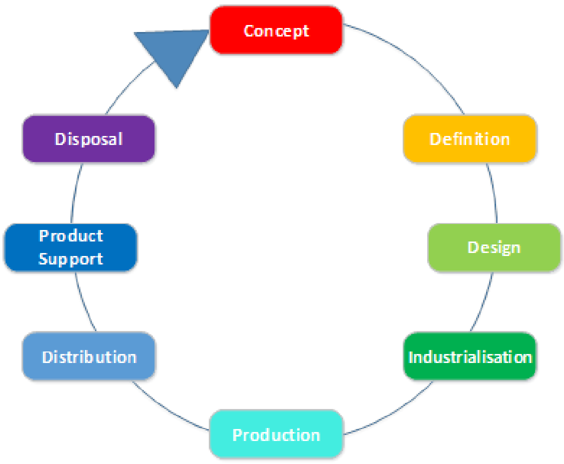

Figure 1.1: Product Lifecycle. Source: du Preez et al. (2015: 28)

It is worth noting in this definition of PLM (du Preez et al., 2015) is that it emphasises the efficiency and effectiveness of the interrelated end-to-end sub-processes for delivering a product. Thus, PLM is focused on managing the product from the beginning of its life to its end of life. This definition presented by du Preez et al. (2015) also highlights the overlap that exists in the definitions of PLM and supply chain. Though its constructs (i.e., product design, manufacturing, distribution and disposal constructs) bring to the forefront the significant overlap that exists in the PLM and supply chain, these work processes are often dealt with individually. Furthermore, both PLM and supply chain definitions include product design as a construct connected to the manufacturing and the distribution of product constructs (Melnyk et al., 2009; du Preez et al., 2015). This indicates that both work processes should be managed and improved with the product design sub-process as part of their performance management processes.

From the previous descriptions and definitions of these work-processes, of the many factors that affect both supply chain and PLM, two significant factors stand out. These factors are (i) capacity constraints in the manufacturing sub-process and (ii) the treatment of product design as a separate process from the rest of the supply chain processes.

Factor (i) capacity constraints in the manufacturing sub-process identified in this research, also supported by literature, drive the typical thinking in improving supply chain performance. The emerging trend from literature appears to justify the notion that improvements made in manufacturing yield positive results for both the supply chain and PLM work processes. Consequently, manufacturers typically initiate improvement by focusing on increasing the capacity of the manufacturing sub-process. They often do this while paying little to no attention to a connected view that includes product design in the supply chain. Though incomplete, this approach is in line with Hausman's measurement of supply chain performance (Hausman, 2004).

Consequently, traditional approaches to improve supply chain performance rely on operational effectiveness concepts with a heavy emphasis on increased manufacturing capacity (Porter, 1996; Arturo et al., 2010; Andersson & Bellgran, 2015; Ylipää et al., 2017). According to Andersson and Bellgran (2015), capacity is the maximum output a manufacturer can produce. Operational effectiveness concepts have since gained traction and are popular amongst manufacturers (Andersson & Bellgran, 2015).

According to Andersson and Bellgran (2015), operational effectiveness concepts are typically based on the Toyota Production System. These concepts include continuous improvement, empowerment, change management, learning organisation, time-based competition, benchmarking and Total Quality Management (TQM), (Porter, 1996). According to Porter (1996), operational effectiveness (OE) includes efficiency; however, efficiency is not its limit. Porter (1996) adds OE encompasses the practices that enable a company to improve the utilisation of its inputs. For example, this results in reduced defective products and (or) more efficient product development (Porter, 1996).

Although these concepts have been widely used, it is only in the last decade that a fast-moving consumer goods (FMCG) factory capacity has seen a remarkable increase (Industry Week, Custom Research & Kronos, 2016). Fast-moving consumer goods refer to products with a short shelf-life, high consumer demand, or perishable (Gabrielsson, Gabrielsson & Gabrielsson, 2008; Kenton, n.d.). This increased capacity is mainly attributable to developments in manufacturing technologies and approaches (Zheng et al., 2017). These advanced technologies for and approaches to the manufacture and supply of product to the market have resulted in shorter cycle times at lower capital costs (Wang et al., 2017).

Although these advances have reduced capital costs, the manufacturing technology still takes longer to recoup the investment made to procure (sometimes including its manufacture), install and operate (Sinnott et al., 2006). The extended realisation of investments happens because, while the manufacturers' capacities may have increased, the orders do not necessarily grow proportionately. Consequently, manufacturers' capacities surpass product orders to the market. This set up implies the technology operates to fulfil orders at a fraction of its capacity. Then it remains idle for the remaining manufacturing time. Subsequently, this increased capacity affords manufacturers the opportunity to penetrate uncharted markets and allows them to introduce new products (Kubíčková, Votoupalová & Toulová, 2014). Successful entry into these new markets, especially with an existing product offering, requires aligning consumers' preferences profiles to those of their existing consumers (Johns & Pine, 2002).

An emerging avenue is exploring consumer preference data as inputs in product development (Johns & Pine, 2002). Spacey (2017, para. 2) describes consumer preferences (also known as market preferences) as "likes, dislikes, motivations and inclinations that drive purchasing decisions. These complement customer needs in explaining customer behaviour." Consumer preferences include: "convenience, effort, user interfaces, communication & information, stability vs variety, risk, values, sensory, time, customer service, customer experience" (Spacey, 2017, paras 2–11). Considering: consumer preferences, behaviours, and lifestyles is essential to sustain market penetration (Johns & Pine, 2002) and effective competition (Hussain et al., 2013; Li et al., 2015).

Moreover, using consumer preferences as inputs can have outputs such as breakthrough, incremental or platform products (Koen, 2004). Koen describes breakthrough products as products that require new technology inventions resulting in significant changes to the products. Koen describes incremental products as products that involve less risky technologies. Koen also points out these are often seen as cost reductions and improvements to current product lines. Koen further states these products may expand product lines and include existing products that are repositioned in well-established markets. Koen describes platform products as products that fall between the extremes of breakthrough and incremental products—adding that these products are significantly larger in scope and resource requirements than incremental products. The advancements in information and communications technology (ICT) afford manufacturers the opportunity to source consumer preferences that result in developing these types of products.

Alongside the advances in manufacturing technology, ICT has evolved and progressed, creating digital interaction platforms that include Google, Wikipedia, Facebook, Twitter, Hello Peter *inter alia*. These have enabled consumers to generate and store digital data about their preferences, behaviour and perceptions *inter alia* (Matz & Netzer, 2017). Consequently, there is a large amount of data available about consumer preference, behaviour and perceptions (Crawford, 2011). Mithas et al. (2013) refer to this data as big data. Manufacturers who tap into big data will develop a competitive advantage in terms of consumer preferences, behaviour and perception (Tien, 2013; Gandhi, Magar & Roberts, 2014; Tirunillai & Tellis, 2014; Jin et al., 2016). According to Twin (2019), competitive advantages are conditions that enable a company or country to produce a service or product of equal value at a lower cost or superior quality. Moreover, thereby outperform its rivals (Twin, 2019).

According to Porter (1996), competitive advantage is achieved by selecting the best combination of activities. Porter (1996) adds that these activities result in strategic positions that lead to competitive advantage. Porter (1996) further suggests these strategic positions are not mutually exclusive and include:

i) *Variety-based positioning*: is based on producing a segment of products or services an industry offers instead of following consumer segments and only fulfils a subset of the consumers' needs.
ii) *Needs-based positioning* addresses the varying needs of groups of consumers (consumer segments) by customising sets of activities that best fulfil those needs.

iii) *Access-based positioning: is* based on the different activities required to reach customers effectively.

Big data allows manufacturers to explore the various strategic positions they can assume to leverage the desired competitive advantage. Although big data has great potential to contribute to strategy and operation in value creation, empirical evidence is insufficient to measure the magnitude of the potential contribution (Niebel, Rasel & Viete, 2017). Therefore the purpose of this research paper is to present empirical evidence in this regard.

Wang et al. (2017) extend the definition of big data offered by Mithas et al. (2013) to include: information collected by companies about sales, the majority of all transactions conducted and operations. Li et al. (2015) and Rüßmann et al. (2015) highlight this operational big data includes real-time data from product monitoring and tracking to equipment management data.

Equipment management data refers to the data collected from activities concerned with the overall manufacturing process, affecting product quality and energy consumption (Li et al., 2015). Li et al. (2015) suggest that this data is useful for, among other things, predicting equipment wear and for reducing energy consumption. The resulting prediction models from equipment management data can be used to plan for engineering maintenance; therefore, directly impacting plant utilisation.

Plant utilisation (PU) is defined as the proportion of time a manufacturing plant uses (Muchiri & Pintelon, 2008; Vorne Industries, 2019). PU is analytically measured as the ratio of planned production time to all time, 24 hours per day/7 hours per week (365 days per average year, adjusted accordingly for a leap year), time which accounts for every second of every day (Muchiri & Pintelon, 2008). Since all time is a fixed duration, maximisation of plant utilisation is achieved by maximising planned production time. Three factors reduce planned production time:

i. legal non-operating time,
ii. plant shutdown due to maintenance, and
iii. the lack of demand, i.e. no orders for a product from the plant, requiring the plant to run (Muchiri & Pintelon, 2008).

Equipment management data supports the process of reducing (ii) plant shutdown due to maintenance, owing to the fact that predictive models derived from this data can result in the generation of pre-emptive maintenance interventions. These interventions can lead to the reduction of (ii) planned shutdown due to maintenance.

While it is possible to increase utilisation by, for instance, using lights-out manufacturing technologies over the legal non-operating time. According to Wamecke and Steinhilper (1985) and Shaiken (1985, cited in Brann, Thurman & Mitchell, 1996), lights out manufacturing technology refers to systems in which manufacturing takes place without human involvement. Brann, Thurman and Mitchell (1996) say these are systems in which: robots, intelligent work cells, automated material handling systems, and computer-based distributed controllers manufacture autonomously.

Although promising great benefits, lights out factories do not fully address the factor (ii) the treatment of product design as a separate process from the rest of the supply chain processes. The critical link between big data (sourced from consumer preference data and equipment management data) and maximised plant utilisation emerges from this discussion. This research, therefore, investigates the factor (ii) focusing on maximising plant utilisation and using equipment management data with market preference analytics derived from big data; thereby, countering (ii) plant shutdown due to maintenance and (iii) the lack of demand.

The availability of this data (big data) on electronic platforms affords manufacturers the ability to collect the data faster. Subsequently, to process and convert it to real-time intelligence and insights about consumers (Tirunillai & Tellis, 2014) as well as manufacturers' operations. The lack of effective means to analyse unstructured, scattered, repetitive and isolated data accounted for small-and-medium-sized manufacturing enterprises' inability to derive value from the data (Tao et al., 2018). This lack of tools for analyses necessitates the use of big data mining capabilities. Big data mining capabilities can extract intelligence and insights about consumers, products and equipment from big data.

Data mining capabilities, according to Crawford (2011), are the functions associated with data mining, i.e. data discovery and includes:

i. Anomaly detection: this function identifies outliers and deviations,
ii. Association rule learning: searches for correlations between variables and is also known as market basket analysis,
iii. Clustering: identifies groups and structures in data that have similarities using uncommon structures in the data,
iv. Classification: generalises known structures to apply to new data,
v. Regression: determines a function that results in a model with the lowest possible error.
vi. Summarisation: summarises the data set by using tools such as visualisation and report generation.

Manufacturers can utilise data mining capabilities in a pro-active supply chain and PLM design process. Pro-active design can be achieved because of the outputs from data mining capabilities that can easily result in product design. Outputs of data mining capabilities can be used to develop predictive analytic models that extract consumer preferences from big data and predict the demand for manufactured products (Yin & Kaynak, 2015; Wang et al., 2017). These models can lead to product innovation and new product development (Yin & Kaynak, 2015; Wang et al., 2017). Product design initiates product development (du Preez et al., 2015).

Li et al. (2015) describe product design as a complex decision-making engineering process that is iterative. It starts with the identification of a plethora of needs. Then progresses through the completion of a series of activities aimed at determining the optimal solution to the problem. Li et al. (2015) state the process is concluded when a detailed product description is achieved. Big data is of interest in this research because it presents the voice of the consumer in its crudest form so that it can be used in a proactive design process. The use of big data enables, to a large extent, the elicitation and identification of the consumers' needs for the product design process.

The new products that result from the variety of specifications arising from market preferences necessitate a shift from mass production. Nair and Boulton (2008) affirm that changes in industry size and technologies can necessitate reconstructing the operation strategy. This view is in line with Mourtzis and Doukas's (2014) view that manufacturing models are configured to serve specific market and economic situations. To take advantage of economies of scale as an operational strategy, mass production focuses on the manufacture of a limited number of product variants (Moeslein & Piller, 2002), thus, rendering it unable to meet customisation requirements.

Moreover, mass production does not presently consider the voice of the consumer at the product design phase. However, it considers the consumer’s voice at the evaluation phase, which occurs post-manufacturing (Zhou, Ji & Jiao, 2013). This post-manufacturing feedback is a reactive design approach. Furthermore, these traditional manufacturing approaches do not consider individual consumer preferences, behaviour and perceptions during the product design phase. They typically take a standardised aggregated response approach, which typically favours the majority response (Zhou, Ji & Jiao, 2013). Thereby miss the opportunities presented by the outliers' responses and limiting the strategic positions that a manufacturer can assume.

To service the outliers, manufacturers require flexibility. The major hurdle faced by traditional manufacturing lies in its inherent constraint of inflexible manufacturing systems. This inflexibility impedes its ability to meet market preference demand. These systems' inflexibility attributed mainly to the complexity recently introduced to their structures and control systems (Zuehlke, 2009). The complexity has led to the current inflexible monolithic manufacturing systems (Zuehlke, 2009). Mourtzis and Doukas (2014) postulate that mass production configurations or their analogies are neither suitable to manufacture all types of products nor able to attain all competitive strategic positions. Hence, these systems fail to reach the goal of TQCSEFK (fastest Time-to-market, highest Quality, lowest Cost, best Service, cleanest Environment, greatest Flexibility, and highest Knowledge), (Li et al., 2015).

Accordingly, overcoming the inflexible monolithicity necessitates higher operating costs for manufacturers to enable them to meet market needs in a short time (Zuehlke, 2009; Zhou, Ji & Jiao, 2013). These higher costs are associated with the required investments into plant modifications, i.e., changes that enable the desired flexibility functions from existing systems. These modifications are often not financially viable. To the envisaged end, the traditional mass production of a single-type product will at best diminish to a minimum, with the worst-case being obsolescence. In contrast, mass customisation and (-or) privatisation manufacturing will rise as the future of manufacturing (Zheng et al., 2017).

Da Silveira, Borenstein and Fogliatto. (2001) submit that mass customisation (MC) is a competitive means that provides each consumer with personalised products. By leveraging high process flexibility and integration, at efficiencies competitive to those of mass production (Kotler, 1989; Fogliatto, da Silveira & Borenstein, 2012). Furthermore, MC is defined by Wang et al*.* (2017) as delivering customised products on a large scale in an interactive manner, thus, satisfying each consumer's specific need at a reasonable price. Its tools can significantly enable product personalisation (Montreuil & Poulin, 2005).

Moreover, Wang et al. (2017) purport that consumer interaction facilitates product design and associated manufacturing. This interaction inherent in MC is integral to value co-creation between the manufacturer and the consumer for all the lifecycle stages of a product. Study (n.d.) defines value co-creation as the strategic act of promoting active engagement coupled with the engagement of the consumer in the creation of on-demand and made-to-order products. Therefore, it is a collaboration of the manufacturer with the consumer and the result that satisfies the consumer's needs as well as the manufacturer's constraints. Thus, it creates value at a reduced cost. This interception of interests between those of the manufacturer and the consumer is a point of interest. It begs the question: can big data be considered a sound source of information in the interaction for market preference-based product design; manufacturing equipment design; and operation to maximise plant utilisation? In this research, this question pursued.

This research's relevance is, in part, validated by the fact that it explores the functionalities presented by the Fourth Industrial Revolution (4IR) era. 4IR refers to cyber-physical systems, which are schemes that integrate computational and physical capabilities that humans can engage with on new modes (Tan et al., 2012; Davis, 2016). These functionalities direct the industrial productivity of the present manufacturing paradigm (Rüßmann et al., 2015). According to Rüßmann et al. (2015), these 4IR functionalities include: (1) autonomous robots, (2) simulation, (3) horizontal and vertical system integration, (4) the industrial internet of things, (5) cybersecurity, (6) the cloud, (7) additive manufacturing, (8) augmented reality, and (9) big data and analytics.

Additionally, the need for this present research further gains legitimacy from the present technological context, 4IR. This research's legitimacy is derived from how it explores the employment of these functionalities, which can culminate in some of this era's ambitions. MC achieves this by exploiting and enabling advanced manufacturing functionalities. Through these advanced functionalities, MC integrates the voice of the consumer (VOC), data analytics and high-performance technology with possible combinations in horizontal as well as vertical systems integration.

The opportunities to integrate are often seen as exclusively applicable to the supply chain sub-processes that occur after the product design sub-process (Khan, Christopher & Creazza, 2012). However, the overlap in the PLM and supply chain work processes' constructs and definitions suggest a direct relationship. This integrated approach can streamline the gains made in efficiency and effectiveness that result from integration opportunities. Simultaneously, these opportunities are better leveraged when these work processes are considered in their entirety, i.e. with the connected product design sub-process. Therefore, the product design sub-process must be coordinated with its complementary processes in both the supply chain and PLM work processes.

Li et al. (2015), when considering big data in product lifecycle management, claimed that in slight excess of 1000 research articles relating to big data have been published. O’Donovan et al. (2015) carried out systematic mapping of big data in manufacturing. Among O’Donovan et al.’s (2015) findings, they determined the prominent types of research contribution in big data comprise: theory 26.67%, followed by frameworks 17.33%, platform 17.33%, architecture 12%, process 12%, model 8%, methodology 4%, and tool at 2.67%. The second-largest body of research knowledge covers frameworks. This research investigates a conceptual framework and positions this work in this category of research knowledge.

The proposed conceptual framework (as presented in figure 1.2) intends to further explore the opportunities in using consumer preference for manufacturers in the FMCG industry. This proposed conceptual framework superimposes product development's interception with a supply chain (SC) and product lifecycle management (PLM) constructs. Therefore, it reconnects the product design process to SC and PLM work processes to maximise the integrated approach's benefits. Extant literature shows common practice views product design separately from both SC and PLM.

In this research, SC and PLM are considered as directly related as supported by the definitions tendered by Melnyk et al. (2009) and du Preez et al. (2015) for the two work processes in their respective works. Subsequently, this research proposes a coherent alignment between the presently discretely treated sub-process of product design in SC and PLM work processes. This end is proposed to be achievable by using big data to assume strategic positions that lead to competitive advantage through higher plant utilisation.

The conceptual framework covers the intersecting constructs, excluding the construct of "disposal of the product" from the definitions of supply chain and PLM work processes. The construct does not form part of this study and may be investigated in future studies. This approach is the chosen approach to maximise the realisable value from opportunities that emerge from the consulted literature and practice. The conceptual framework is depicted in Figure 1.2.

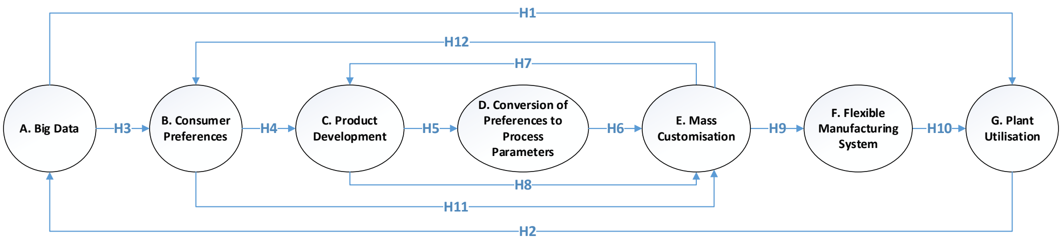

Figure 1.2 Conceptual framework on the use of big data for product development in mass customisation. Source: (Author's own)

The following section discusses each of the constructs in the proposed conceptual framework shown in Figure 1.2. The hypotheses are not discussed in this section, but in Chapter 2. However, the linkages of the constructs are discussed.

[A]. **Big Data:** represents voluminous, scattered and unstructured data as it occurs on ICT platforms (Rozados & Tjahjono, 2014; Yin & Kaynak, 2015; Jin et al., 2016). This data grants manufacturers direct first-hand access to the voice of consumers about experiences with various products (Nam, Joshi & Kannan, 2017). This preference data includes information on demand for existing products as well as specifications expected of future products. Typical customer requirements (CRs) collection for the product development process uses interviews, questionnaires, or surveys. Whereas online interaction platforms including social networks, blogs, and product reviews *inter alia*, disclose consumer preferences thus, enabling designers to collect CRs, analyse trends, and benchmark versus competing products (Crawford, 2011; Jin et al., 2016). Matz and Netzer (2017) posit big data analytics can be used to derive valuable insights into consumers' psychological states and traits. Manufacturers can use these insights to determine which products are on recurring demand, frequency of the demand, and anticipate for recurrence and frequencies of demand. Additionally, correlations between the psychological states and traits to demand for the respective products can be formed. Buxton (2011) defines demand as a function that represents the behavioural patterns of both actual and potential buyers of a particular good. The apparent correlations can be used to model demand amongst other related consumer behavioural phenomena. However, in big data these insights occur in unstructured data form.

The insights can only be extracted through data mining techniques (Crawford, 2011). Some of these data mining techniques include text mining and tag-mining, which extends to geotagging. The latter affords further insights on the geolocation (the location at which the experience took place) of the experience (Fan & Gordon, 2014; Nam, Joshi & Kannan, 2017). For instance, a consumer who is (dis-)satisfied with the quality and (or) stock level of a product or service records this information on an ICT platform. The information would typically include the names of the product name, brand name, merchant name, the product characteristic that causes the (dis-)satisfaction, and location. Moreover, the latter can be obtained by extracting geolocation data.

From these data points, manufacturers can generate more accurate and (or) improve the accuracy of their current predictive analytical models (Yin & Kaynak, 2015). Crawford (2011) agrees there is value inherent in big data. This value is perceived to be greater than is currently derived from existing information-gathering systems.

In addition to using consumer opinion for eliciting market preference data, Johanson et al. (2014) show big data can be derived from performance data and base customer requirements pertaining to how the product is used, i.e. consumer behaviour. Johanson et al. (2014) and Zhang et al. (2017) make use of data collected from product embedded information devices (PEIDs). PEIDs include smart sensors and tags on the product (Zhang, Ren, Liu, Sakao, et al., 2017). This information can be used to identify the consumer's behaviours, subsequently linking these to product attributes that cater to the observed behaviours.

Let us consider the link from [A] big data to [G] plant utilisation. The data points can be used in production scheduling. Production scheduling is defined as the activities performed to manage and control the manufacturing process (Fera et al., 2013). Managing and controlling of processes is typically managed with the intent to drive increased [G] plant utilisation, thus, linking [A] big data to [G] plant utilisation. This link can assist in detecting emergent market trends, root cause analysis for failures, issues, and defects (Hassani & Silva, 2015).

Therefore, the extraction of useful data from [A] big data links to both [B] consumer preferences and higher [G] plant utilisation. Stone (1980) describes these two linkages viz. (1) the link “between quantity of the product demanded and variables such as price, income of buyer, advertising expenditure, and so on.” (relates to the link between [A] big data and [G] plant utilisation). Chase (2013) supports this view and presupposes an opportunity to improve demand forecasting and production planning using big data exists. Further, Chase (2013) elaborates big data analytics, from market activity, make it possible to pick up demand signal, determine optimal prices and trace consumer loyalty. (2) “analyses buyers’ demand for product characteristics and how this demand is translated into demand for particular products (e.g. how demand for comfort, speed, acceleration capacity, etc. arises and is translated into demand for particular kinds of transport)” (relates to the link between [A] big data and [B] consumer preferences) (Stone, 1980: 54). Based on this evidence, the linkage between [A] big data and [G] plant utilisation can be made.

Next, let us consider the link from [G] plant utilisation to [A] big data. This link relates to the information about the plant’s available resources and equipment management data. This data can be factored into the [A] big data construct. In this scenario, data about [G] plant utilisation, for example, includes equipment management data, resources, capacity, performance capabilities, etc. It also contains valuable data which can be stored into [A] big data constructs. Croxton et al. (2002) refer to this process as demand management. Croxton et al. (2002) defined it as the supply management process that relates to balancing consumers’ requirements with the supply chain's capabilities. Based on this, demand management can integrate big data as a source of decision making. By doing so, the right balance between the supply chain capabilities and consumers’ requirements is pursued to maximise plant utilisation.

In addition to this, data on [G] plant utilisation being used to further improve production scheduling. When deciding on new products to increase product orders, the [G] plant utilisation data can help identify the relevant consumer data. For instance, a plant’s capability at a time is fixed by the resources of the plant. From the available plant’s resources, product development can work backward. It can be assessed from the consumer preference data, which would be best catered for by the current configuration (Labbi, Ouzizi & Douimi, 2015). This exercise can be conducted to reduce the need to redesign and (or) make changes to the plant's resources. The result of this exercise can be an addition of a product or products to the product portfolio, which in turn may increase orders, and thus maximise [G] plant utilisation. This approach contrasts to traditional methods that use forecasting techniques and carry inherent errors (Winston & Goldberg, 2004), thus, are more prone to waste.

Next, let us consider [A] big data linking to [B] consumer preferences.

[B]. Consumer Preferences: (also known as market preferences in this research) in so far as they relate to both intrinsic and extrinsic product/service attributes (or characteristics). The former attributes engage all human senses, viz. appearance, smell, texture, sound, and taste. In comparison, the latter attributes are concerned with the consumer's visual sensation, viz. brand, packaging, label, price (Symmank, 2019). These preferred product attributes can be extracted from [A] big data through big data analytics (BDA). BDA concerns the application of data mining capabilities on [A] big data sets (Elgendy & Elragal, 2014; Rozados & Tjahjono, 2014). Thus, BDA presents the insights gained from the unrestricted rich sources of consumer preferences. These are then presented without the size limitations often imposed by sampled data. This richness is further augmented by the fact that consumer preferences are posted and retrieved from social media platforms without purposeful guidance (Jin et al., 2016). In this research, BDA containing consumer preferences (market preferences) refers to market preference analytics.

Since the market preference analytics contain valuable [B] consumer preference data, manufacturers can use them to improve consumer requirements (CRs). According to Zigu (n.d.) CRs comprise service requirements and output requirements. The former pertains to intangible elements of the experience of purchasing products expected by a consumer. Whereas the latter elements are concerned with tangible characteristics, features, or specifications expected of the product by the consumer (Zigu, n.d.).

The use of market preference analytics to generate CRs (Jin et al., 2015) strengthens the quality of the resulting defined CRs, which form the basis for [C] product development. Moreover, it augments the voice of the consumer and embeds it in the product design process. The richness of the source data enables the design of products to fulfil a larger market's needs. Additionally, satisfying the consumers to a greater extent than products developed from sampled data collection and analyses methodologies. Sampled data processing methodologies result in manufacturers servicing a portion of the market. This reduced market results from the sampling methodologies that provide information on data points where the occurrences of preferences are concentrated, i.e., central tendency measures. Contrastingly, data mining capabilities can handle data from the whole population. Moreover, they produce market preference analytics reflecting insights on the whole population.

Since market preference analytics are generated from more extensive data sets of the population. Its output can include, among other things, hidden consumer patterns in the data. These patterns can reveal correlations in extrinsic and intrinsic attributes to the population of consumers. The emerging correlations can be used to identify key product attributes, for example, a clustering exercise. The uncovered correlations can be insights that lead to breakthrough, incremental or platform products. It then follows these resultant products would satisfy the preferences of the population to a more considerable extent.

Moreover, consumer preferences can be the source of the various parameters and criteria for designing and manufacturing [E] mass customisation manufacturing equipment and resulting processes. These preferences can be used to determine how far the design and manufacture of [E] mass customisation manufacturing equipment can be pushed.

For instance, limitations imposed by manufacturing equipment and (or) process can help refine the CRs used as a basis for [C] product development. This link results in an iterative loop between [B] consumer preferences and the manufacturing equipment's design referred to as [E] mass customisation.

Both opportunities for product innovation and new product development can then result in a more diversified product category. Either or both opportunities would increase the product volumes to be run by the plant. Consequently, reducing a plant’s idle time and subsequently improving the [G] plant utilisation.

In contrast, the traditional approach of eliciting public opinion after manufacturing often leads to costly plant modifications, retrofits, and capability exercises building of the plant personnel. These changes manufacturers typically implement as attempts to accommodate newly acquired market insights linked to market dynamics.

Whereas [B] consumer preferences big data links to this rich information from the outset. This connectedness can lead to proactive product and plant design resulting in improvement benefits and competitive advantage. This approach's outcome is a design process that integrates market preference analytics into its manufacturing equipment and processes design. Moreover, this design process builds into its supply chain some flexibility that allows the manufacturer to respond to market dynamics faster and become more resilient.

Now let us consider [B] consumer preferences linking to [C] product development.

[C]. **Product development**: virgin CRs extracted from [B] consumer preferences, these are unguided by design and (or) manufacturing constraints and merely represent consumers' desires in their raw form (Crawford, 2011; Jin et al., 2016). These consumer preferences are then used to determine the optimal product architectures. Ulrich (1995) elaborates on the definition of product architecture from merely the mapping of product functions onto physical components; to include the following aspects (i) the arranging of functional elements and (ii) the specifying of the interfaces for the interaction of the physical components.

Now let us consider the links [E] mass customisation to [C] product development. The limitations arising from the [E] mass customisation step can be used as selection criteria developed from [B] consumer preferences to separate the viable product attributes from the unattainable. Furthermore, they can be used to aid the development of limits for feasible product architectures. Altogether these can be used to inform the iteration and design of product families. "Product family design and development essentially entails a conceptual structure and overall logical organisation of generating a family of products by providing a generic umbrella to capture and utilise commonality, within which each new product is instantiated and extended so as to anchor future designs to a common product line structure" ((Roger) Jiao, Simpson & Siddique, 2007: 6). The resulting product attributes from the final product architectures and families can then be used in the [D] conversion of preferences to process parameters.

Next, let us consider the link from [C] product development to [E] mass customisation. The product architecture and family development information from [C] product development can be used to further guide the [E] mass customisation process. This information can then be used to explore and generate a repository, for instance, of design boundary possibilities for both current and future MC equipment designs. These possible designs can be explored primarily for maximising plant utilisation amongst other design objectives.

The proposed links between [C] product development and [E] mass customisation are interrelated, leading to a bidirectional and iterative linkage. This interrelatedness implies the procedure can be conducted until convergence is reached at the desired optimal design outcome maximised plant utilisation.

Next, let us consider [C] product development linking to [D] conversion of preferences to process parameters.

[D]. Conversion of Preferences to Process Parameters: The product family and product architectures, which emerge from [C] product development, are then converted to processing parameters viz. engineering characteristics (ECs). According to Hauser and Clausing (1988), ECs express the CRs quantitatively and directly affect customers' perceptions. Popular approaches widely applied in the conversion of CRs to ECs include the Conjoint Analysis, Quality Function Deployment (QFD), and Kano Model (Jin et al., 2016; Qi et al., 2016).

The conjoint analysis is a tool used to approximate the structure of CRs (part worth, importance weights, ideal points) based on the customer's overall assessment of predefined alternatives presented in terms of the levels of the various attributes (Green & Srinivasan, 1978).

Jin et al. (2016) describe the QFD as a tool often used with a planning matrix to link CRs (state and unstated) to ECs and yield the values of ECs. Although it is found to be very useful, it is criticised for not being able to balance the importance of CRs. Hence, it is used in conjunction with the analytic hierarchy process (AHP) to balance the relative importance of CRs (Jin et al., 2016). The AHP is a structured technique for organising and analysing complex decisions based on mathematics and psychology (Moktadir et al., 2019). Li et al. (2015) suggest there is a need for the QFD approach to evolving it to enable it to meet the challenges presented by [A] big data. Moreover, it needs to be enabled to manage the intricate correlations that exist between function and needs (Li et al., 2015).

The Kano model is used to measure the impact of CRs on customer satisfaction (Zhu et al., 2010). The Kano model uses five main product attribute classifications as stated by Qi et al. (2016) viz.: 1) *Must-be quality*, which captures the basic product criteria. The absence of these results in high customer dissatisfaction levels; however, their presence does not increase customer satisfaction. 2) *One-dimensional quality* improve customer satisfaction levels, while their absence proportionally reduces satisfaction levels. 3) *Attractive quality* carries signature quality differentiation amongst competitors; these contribute to absolute satisfaction levels, their absence does not influence dissatisfaction. 4) *Indifferent quality*, these attributes have no bearing on customer satisfaction, whether present or not. 5) *Reverse quality*, the presence of these attributes is harmful to the customers and should be removed.

In the last 20 years, industries have introduced quality management systems and standards, including Quality Control Circles, ISO 9000, Total Quality Management, among others. These have been introduced to achieve customer satisfaction (Kondo, 2001). Furthermore, through these systems, firms secure the consumers' long-term loyalty by manufacturing products and providing services that, at the very least, meet, and at best, exceed their expectations (Zhu et al., 2010). The use of these techniques presents the prioritisation of CRs, which determine the ECs that can be tested and fixed in the [E] mass customisation process.

Next, let us consider [D] conversion of preferences to process parameters linking to [E] mass customisation.

[E]. **Mass customisation:** in this research refers to equipment design and optimisation. This exploration primarily hinges on the use of the ECs from [D] conversion of preferences to process parameters. A secondary contribution is from the outputs of [C] product development which are considered at this stage to push the boundaries of the design and manufacture of products. The equipment design and optimisation activities are conducted with the objective to maximise flexibility and product diversity the plant can manufacture at maximised utilisation.

Next, let us consider [E] mass customisation linking to [F] flexible manufacturing systems.

[F]. **Flexible Manufacturing System:** the critical enablers for flexible manufacturing systems (FMS) are routing and machine flexibilities driving the manufacturing processes (Yildirim & Yücel, 2016; Mahmood et al., 2017). Routing flexibility refers to the system's ability to be modified in order to be able to produce new product types. In comparison, machine flexibility refers to multiple machines' abilities to carry out the same operation on a part. FMS is proposed as a means to address the continually changing needs of production and operations as directed by dynamic customer needs (Shang & Sueyoshi, 1995; Al-Kahtani et al., 2014; Yildirim & Yücel, 2016). FMS can enable manufacturers to address the inflexibility constraints the current mass production systems impose.

As discussed earlier, these traditional systems cannot cater to diversity in market preferences. These systems cannot fulfil market preferences at high plant utilisation levels and are cost-ineffective. As a result, this can threaten the competitive advantages mass production manufacturers currently enjoy. However, FMS overcomes this by making use of programmable machines with an integrated automated material handling system (MHS) with a central controller to produce a diversity of parts at wide-ranging production rates, batches and volumes (Leondes, 2003; Ali, Qureshi & Jahanzaib, 2013).

From [E] mass customisation, the resulting feasible optimised manufacturing plant is then constructed, commissioned, and run in the form of FMS. At this point, [E] mass customisation goals are attained by using [F] flexible manufacturing technologies which increase plant utilisation.

Next, let us consider [F] flexible manufacturing system linking to [G] plant utilisation.

[G]. Plant Utilisation: the plant is scheduled and run to achieve maximum [G] plant utilisation through the optimisation of [A] big data and [F] flexible manufacturing systems to reduce the amount of time the plant is idle. Yildirim and Yücel (2016) support this view, listing the advantages that FMSs yield, among other things: improved capital and equipment utilisation ([G] plant utilisation); reduced work in progress and set up; significantly improved throughput and lead times; reduced inventory and smaller batches and reduced workforce. Thereby improve the required performance of the supply chain and of the associated PLM.

Furthermore, Tiwari et al. (2018) show the consumer supply chain accounts for 8% of big data analytics usage, banking supply chain 43%, followed by technology and healthcare at 14% and 11%, respectively. This study focuses on the consumer supply chain as the research shows the low usage of 8%. The lower usage indicates much-unexplored territory for development, usage and improvement for firms that aspire to assume competitive advantage positions. This low uptake motivates the focus on the fast-moving consumer goods industry, which constitutes the consumer supply chain.

In summary, there are opportunities for FMCG manufacturers to improve their strategic positions to capture competitive advantages in the operations of their full supply chains and PLMs. These require a departure from the traditional mass production operational improvement programs aimed at manufacturing capacity. These approaches use the 4IR functionalities to capture valuable information from various big data sources for the design and operation of competitive supply chains. This information is pertinent for the design and operation of flexible manufacturing systems to maximise plant utilisation.

In the following section, the problem and motivation for the present research are discussed.

1.2 Problem Statement/Motivation

Manufacturers have an abundance of rich data available. However, they are unable to link the data to achieve maximum plant utilisation (Tao et al., 2018). This is the case even though these big data sources directly affect plant utilisation levels. As discussed in the preceding section, this big data carries, amongst other things, insights on the performance of current manufacturing equipment and market preferences data. This big data, when appropriately processed, can secure manufacturers' competitive advantages well into the future.

Also discussed earlier, there is little to no evidence that equipment management data is used together with market preference analytics in production scheduling. Production scheduling aimed at maximising plant utilisation is based on forecasting models constructed from sampled historical data used and not on either near- or live big data.

In addition, at present, product design is conducted with information sourced through focus groups, questionnaires and surveys; typically, results with the specifications of the final product that are determined by preferences of the majority of the sampled population (Zhou, Ji & Jiao, 2013). This aggregated response-based design imposes constraints on product differentiation that translate to limited product categories and constricts market penetration. This constricted market penetration reduces product demand orders that the plant manufactures at a fraction of its capacity, thus, adversely affecting plant utilisation.

Using market preference analytics to design products and the related mass customisation activities promises to attenuate the challenges relating to product categories encountered in market penetration efforts. This approach to design can lead to the design and operation of FMS. Moreover, the same market preference data can be used alongside equipment management data in production scheduling. This connectedness can lead to maximised plant utilisation amongst other competitive advantages.

This study aims to close the gap for manufacturers, in FMCG, across its supply chain and PLM by investigating the proposed framework.

1.3 Research Question

The 4IR era has availed functionalities that have not previously been available to manufacturers, and their respective supply chains, to improve productivity. These functionalities have shifted the context of manufacturing. Furthermore, these new technologies have enabled more efficient ways of doing things, particularly for information gathering and insights generation. This efficiency in data and insights systems strengthens the manufacturer's intelligence about the consumer, giving finer resolution to previously granular data on customer preferences through big data mining. It allows the manufacturer to build this intelligence into their product lifecycle and supply chain development as well as management processes. This approach reduces manufacturing costs while raising the value for the consumer. Consequently, it maximises the value for the consumer while reducing the manufacturing costs.

The research question is:

How can a framework be developed linking big data to flexible manufacturing system design leading to maximised plant utilisation?

1.4 Research Objectives

The appropriate framework constructs (or nodes) must be identified to arrive at the overall practical and efficient framework design. Subsequently, the correct linkages must be made between the product development sub-process and big data and then to the design of the supply chain and product lifecycle management work processes. Moreover, this process needs to be optimised and lead to maximised plant utilisation. It follows then that the objectives of this research are to:

i. Determine the constructs to be included in the framework for using big data to improve utilisation.
ii. Determine how big data can be linked to plant utilisation.
iii. Determine the impact of consumer preferences on the equipment design and how the consumer preference data affect the design constraints.

1.5 Summary of Research Method

To address the research question, the study followed a two-phased approach to:

Phase I: During this phase, a survey of the literature was conducted to identify the constructs to be included in the framework that links market preference analytics to maximised plant utilisation. From the literature survey, the round one (1) qualitative Delphi study questionnaire was constructed.

Phase II: This phase was marked by the roll-out of the round two (2) Delphi Study administered online. The initial round responses, feedback and analysis, were used to construct the round two (2) quantitative questionnaire. This quantitative questionnaire was also administered online. The results from the Delphi study were analysed, and conclusions were drawn from them.

The primary focus of this investigation is phase II. The initial phase was used as the foundation for the final phase of the Delphi Study.

1.6 Limitations

This study has focused on active users of digital ICT interaction platforms to extract market preference-based analytics. The study thus excludes the population that is not on digital ICT platforms. The study focuses on the collection of data to extract consumer preferences for the FMCG industry exclusively.

1.7 Assumptions

In this study, it is assumed that the panellists answered questions truthfully despite the confidentiality and (or) sensitivity of the information, where applicable. This assumption is thought to be reasonable. On the basis that upon undertaking to respond to the online surveys, panellists consented, understanding the data collection and reporting are built on privacy, anonymity, confidentiality, and voluntary participation. Furthermore, it is assumed the sampled panel meets the requirements prescribed for a Delphi Study. This assumption is deemed reasonable because the sample comprises experts from various functions and organisations within the FMCG industry's supply chain.

1.8 Research Report Outline

Chapter 1: The purpose of this chapter is to provide the context, justification, and scope of the research. From the context discussion the justification of the investigation arises then the conceptual framework is presented with the supporting literature as theoretical basis. The proposed conceptual framework contains the constructs as identified from literature with the respective linkages. The problem statement carries from the brief theoretical resume and followed by the limitations of the study.

Chapter 2: The purpose of this chapter is to present the theoretical grounding of the linkages between big data construct and the mediating constructs leading to maximised plant utilisation. This is achieved through an assessment of literature relating to the various constructs and related linkages as they appear on the proposed conceptual framework. The linkages are then presented as hypotheses.

Chapter 3: In this chapter, the research methodology is presented. The critical analysis of the required paradigm is presented with supporting literature. A discussion on the design of the research, sequential exploratory mixed research method, follows the analysis of the paradigms. Thereon, the Delphi Technique's history is presented with the literature on its features that align with the research method design. Discussions that follow on from this Delphi Technique survey include the panel selection, research instrument, analyses and interpretation, and validity and reliability. The chapter then presents a statement on ethics.

Chapter 4: The purpose of this chapter is to provide answers to the research question. This is achieved through the analysis and review of the opinions solicited from the Delphi Study. The hypotheses test results are reviewed and discussed.

Chapter 5: The purpose of this chapter is to present insights drawn from the results. These insights are discussed against the objectives of this study, the results collected and extant literature.

Chapter 6: The purpose of this chapter is to present conclusions drawn from the study as it relates to the research question and the objectives of this study. Furthermore, the implications of the study are presented as they apply to government, practitioners as well as to academia.

CHAPTER 2: LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Introduction

In this section, the literature about the constructs identified for the conceptual framework depicted in Figure 1.2 is explored. In this literature survey, the application of big data (through market preference analytics) in the respective sub-processes of PLM and supply chain (manufacturing and distribution) is at first approached separately. Notwithstanding, later in the chapter, literature that develops the seemingly discrete constructs' intersection is reviewed. This approach is chosen because most of the literature consulted for this research report addresses the constructs of the product design and subsequent constructs of the supply chain and PLM independently. This review's layout progression is in the sequence of the constructs included in the conceptual framework in Section 1.1.

Figure 1.2 is presented here for the sake of clarity, and the figure has already been introduced in the Introduction section 1.1.

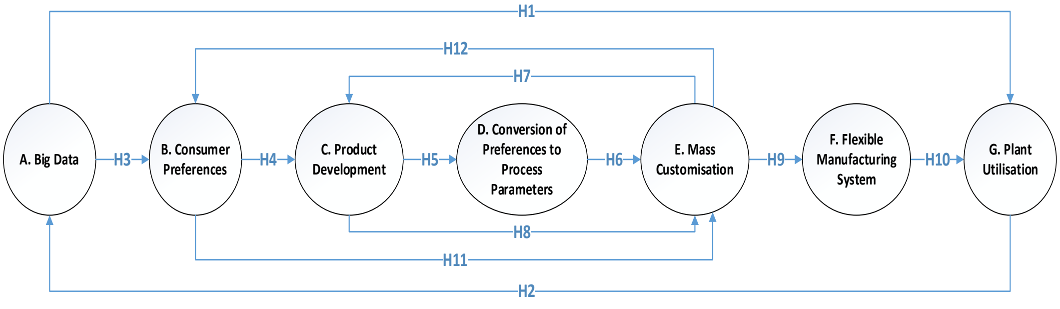

Figure 1.2: Conceptual framework on the use of big data for product development in mass customisation

As stated earlier, the literature review follows the sequence of the model viz. market preferences analytics from big data sources are considered (2.2). This sub-section is followed by a review of the product design's alignment to the PLM and SC (2.3). The role of mass customisation follows (2.4) and the enabling features of FMS (2.5). The section is concluded with the hypotheses that emerge from the proposed model (2.6).

2.2 **[A] Big Data and Market Preference Analytics from [B] Consumer Preferences**

A large amount of digital data is generated on social networks (Jin et al., 2016). Case in point, Facebook is cited for having processed in excess of 500 TB of information daily in 2012 (Li et al., 2015). Extant literature presupposes there is potentially great value in big data (Fan & Gordon, 2014; Gandhi, Magar & Roberts, 2014; Jin et al., 2016). Consequently, this has sparked immense research interest, which is evident in the rapidly growing body of research in preference data analytics (Bollier, 2010; Provost & Fawcett, 2013; Tien, 2013; Elgendy & Elragal, 2014; Fan & Gordon, 2014; Rozados & Tjahjono, 2014; Li et al., 2015; O'Donovan et al., 2015; Jin et al., 2016; Tiwari, Wee & Daryanto, 2018).

As discussed in Section 1.1, [A] big data related to this study contain consumer preferences and equipment management data. [B] Consumer preferences (also referred to as market preferences), in turn, are composed of consumer opinion (2.2.1) and consumer behaviour (2.2.2). Equipment management data (2.2.3) refers to the equipment's performance information concerning product quality and energy consumption within the manufacturing process (Li et al., 2015). Therefore, equipment management data presents available improvement and optimisation information within a particular manufacturing set up. These performance opportunities are linked to [G] plant utilisation directly.

Also discussed in Section 1.1., both consumer opinion and behaviour data can be inputs to [C] product development, as [B] consumer preferences. Market preference analytics refers to the outputs from applying data mining capabilities on consumer preferences, discussed in Section 1.1. Moreover, consumer opinion and behaviour in their raw form within [A] big data can be used in production scheduling (Stone, 1980; Chase, 2013; Hassani & Silva, 2015). Production scheduling is defined as the activities performed to manage and control the manufacturing process (Fera et al., 2013).

2.2.1 Extraction of Product Development information from Consumer Opinion [A] Big Data

This section relates to the mining of product development and demand information to maximise plant utilisation. This product development information includes product features, and this is obtained from [A] big data. Next, demand information includes consumer opinion and consumer behaviour which are also obtained from [A] big data. In this section, 2.2.1, consumer opinion is addressed. Consumer behaviour is addressed in section 2.2.2.

Jin et al. (2016) posit that consumer behaviour data can lead to an understanding of consumer requirements. Further, Jin et al. (2016) point out this understanding can be obtained using consumer opinion data polarities to identify product features and forecast trends. Consumer opinion polarities refer to distinguishing “negative” from “positive” sentiments on a feature (Do et al., 2019). This consumer opinion data forms part of market preference data that is the basis for market preference analytics. Jin et al.’s (2016) view is supported by Afshari, Peng and Gu (2016), who argue big data analytics are useful for product development. The consumer opinion data has to be collected from various market sources to determine consumer polarities which are necessary for effective design. Next, the various sources of market preference from the related data are discussed.

Nam, Joshi and Kannan (2017) show brand perceptions are insights generated from online communication that consumers use to express their experiences with and perceptions of a brand. These consumer experiences and perceptions are extracted and interpolated to brand perception maps. As a result, the data extracted for brand perception directly relate to market preferences (Culotta & Cutler, 2016). To extract brand perceptions and market preference insights, researchers have suggested different data mining sources. These data mining sources include search data (Ringel & Skiera, 2016), microblog data (Culotta & Cutler, 2016), online reviews (Lee & Bradlow, 2011; Tirunillai & Tellis, 2014) and posts on various online discussion forums (Netzer et al., 2012). Search data refers to the clickstreams of consumers searching for topics across disciplines as well as products (Ringel & Skiera, 2016). Clickstream data logs the detail of how a user navigates through a website when completing a task (Albert, Tullis & Tedesco, 2010). Microblogs include but are not limited to Facebook, Twitter and Instagram (Nam, Joshi & Kannan, 2017).

Approaches to Data Mining

The big data occurs in widely scattered, unstructured, and in various formats; generated across its multiple sources at unprecedented rates with undetermined value (Rozados & Tjahjono, 2014; Yin & Kaynak, 2015; Jin et al., 2016). Nam, Joshi and Kannan (2017) suggest three main approaches to mine data: primary data-based methods, text mining, and social tags mining. Primary data-based methods refer to the traditional means of guided sampled data collection (Nam, Joshi & Kannan, 2017). Text and social tags mining are described in the following sub-sections.

Text Mining is a tool that aids the process of identifying patterns in the raw text then extricate pertinent information from text-based data (Lee & Bradlow, 2011; Netzer et al., 2012; Tirunillai & Tellis, 2014). Text mining tools have yielded marked success in marketing research in the creation of brand-associative networks by automatically identifying keywords from social media platforms' user-generated content. These platforms include posts on online user forums or online user reviews (Lee & Bradlow, 2011; Netzer et al., 2012; Tirunillai & Tellis, 2014). The elicitation stage entails the following steps: cleaning and preparing the text, then extracting the information of interest from the text (Netzer et al., 2012). The approach takes a rule-based approach, a machine-learning approach, or a hybrid of these two methods to extract the information in the text of interest (Netzer et al., 2012).

Social Tags Mining is another popular approach referring to the mining of social tags. Social tags are user derived keywords linked to online content that reflect the consumers' perceptions of objects and classify an artefact, idea, or concept (Nam, Joshi & Kannan, 2017). According to Nam, Joshi, and Kannan (2017), individuals use social tags on social media platforms both to arrange and discover content in line with its topical relevance.

Further, Nam, Joshi, and Kannan (2017) point out that social tags can provide a rich and heterogeneous interpretation of a brand across and within individuals, i.e., [G] consumer preferences. Additionally, Nam, Joshi, and

Kannan (2017) posit that over time individuals' knowledge structures are shaped by their encounters with stimuli (content, interactions and experiences).

Moreover, Nam, Joshi, and Kannan (2017) submit differences in tags different people use for the same content can provide insights regarding the extent of heterogeneity in users' knowledge structures about the brand of interest. This insight renders tags ideal for exploring how users believe, think, feel, and reason about brands (Nam, Joshi & Kannan, 2017). Since brand information is linked to product preferences, this study supposes that brand information is drawn from consumer preferences and vice versa (Culotta & Cutler, 2016).

Shortcomings of the big data mining data approaches

Although these big data mining techniques have shown good promise, Nam, Joshi, and Kannan (2017) highlight the following shortcomings to the approaches:

(i) Primary data-based methods: use consumers' direct input as elicited through surveys, interviews, or sorting tasks characteristically designed to collect brand images/attributes and consequently tend to generate more subjective keywords, be more sensitive to sample size, and often depend on researchers' interpretation.

(ii) Text mining: automates keyword extraction algorithms based on the assumptions of the researcher. This makes the process vulnerable to the knowledge of the researcher.

(iii) Social tag-based approach uses brand associations directly produced by consumers relating to their interactions with brands. This, however, makes brand associations sensitive to consumers' biases and potential social influences, moreover yet capable of capturing them.

2.2.2 Extraction of [C] Product Development Information from [A] Big Data Specifically Consumer Behaviour

Johanson et al. (2014), who worked on Volvo Car Corporation cases, propose a telematics and analytics framework for knowledge-driven [C] product development. Johanson et al. (2014) allude to performance data derived from the handling as well as the use of a product (consumer behaviour) and data from manufacturing equipment and (or) components ([G] plant utilisation). [G] Plant utilisation will be discussed later in section 2.5. From this, Zhang et al. (2017) propose a framework for big data-driven product lifecycle looking at all the aspects of product lifecycle management viz. beginning of life, middle of life, and end of life. Zhang et al.'s (2017) work emphasises and focuses on the big data captured using PEIDs.

According to Zhang et al. (2017), and Do et al. (2019), the programming of PEIDs for manufacturing and product settings allows for collecting diverse big data in real-time and non-real-time configurations. This capability means the data source can be used for [C] product development and [G] plant utilisation. The latter application is a consequence of sensor and RFID tag technologies PEIDs employ.

These outputs can give information about each piece of the equipment on which PEIDs are installed. Similarly, data collected from products can indicate how consumers (and other players in the value chain) handle and use manufactured products. This handling and use data give insights into consumers' behaviour and how they interact with the product. Thus, it gives designers information about the attributes that increase value for consumers in terms of behaviour and use.

Therefore, Johanson et al. (2014) and Zhang et al. (2017) add to the sources from which consumer data essential in [C] product development and [G] plant utilisation can be extracted. Moreover, highlighting this type of big data is generated and extractible.

2.2.3 Extraction of [C] Product Development Information from Equipment Management Data

Tao et al. (2018) claim advances in internet technology, the internet of things, cloud computing, and artificial intelligence have exposed manufacturing to large volumes of data. Internet of things refers to technology that combines sensors, standards-based networks, and smart analytics to enable information flow structuring to optimise manufacturing (Gandhi, Magar & Roberts, 2014; Wang et al., 2017). Cloud computing refers to a model that enables access to computing infrastructure, including but not limited to networks, servers, storage, applications, and services with little management intervention (Mourtzis & Doukas, 2014). Lee et al. (2015) attest to Tao et al.'s (2018) view and add the availability, affordability and use of data acquisition systems as well as networked equipment continue to generate high volume data.

The high-volume data have found various applications in manufacturing. Tao et al. (2018) propose a conceptual framework for data-driven manufacturing from a case study based on silicon wafer production. Lee et al. (2015) propose a guideline to implement cyber-physical systems within manufacturing to improve operational efficiency, resilience, and collaboration. Cyber-physical systems enable human beings to engage with the integration of physical and computational capabilities through various modes (Baheti & Gill, 2011; Lee, Bagheri & Kao, 2015). He and Wang (2018) propose statistical process monitoring to yield manufacturing intelligence from real-time data to improve accurate and timely decision-making. Data mining-driven manufacturing process optimisation using an advanced manufacturing analytics platform is proposed from conceptual use cases by Gröger et al. (2012). This research presents information that constitutes the source of equipment management data (EMD).

Up to this point, this review demonstrates that research has been conducted on sourcing and applying big data from and on the individual sub-processes of the supply chain as well as product lifecycle management work-processes. Where success has been realised, it has led to pockets of improvements within the SC and PLM sub-processes. These improvement pockets accentuate the existing gap in the research, which arises from the lack of a holistic and connected view of the SC and PLM constructs to maximising plant utilisation. The following sub-sections describe research on big data applications on the complete supply chain and product lifecycle management work-processes.

Evidently, consumer opinion (2.2.1), consumer behaviour (2.2.3), and equipment management data (2.2.3) are rich sources for improving manufacturers' respective supply chain design and operation. Despite this, Crawford (2011) acknowledges there exists a view among researchers that big data merely improve the analyses that are conducted on small data. Additionally, this view presupposes data is interchangeable. However, Crawford (2011) argues the context of the data determines its application. Further, Crawford motivates there is no merit to claiming equivalence in datasets even when they can be similarly modelled.

Moreover, Crawford (2011) cautions against the use of big data in research without adequate transparency on (1) the limits of the dataset, (2) the limits that should be imposed when interrogating the data and lastly, (3) the interpretations that are apposite for the considered data. This view is supported by Bollier (2010), who highlights there are inherent errors that exist within datasets, mainly when obtained from different sources. Which, when combined, increase the likelihood of intensifying and propagating the impact of the error in the final analysis. It then follows that data processing integrity determines the derivable value from big data in the extraction of consumer preferences. Although this view exists, growing interest in big data and associated integrating system architectures and technologies include data cleaning processes (Zhang et al., 2017; Nguyen et al., 2018). By incorporating data cleaning processes in the architectures, the pitfalls highlighted by Crawford (2011) and Bollier (2010) proactively addresses the potential errors in the final analyses.

2.2.4 The Use of Big Data in the Supply Chain

The supply chain and PLM work-process constructs considered in this study relate to product development, manufacturing and distribution (Melnyk et al., 2009; du Preez et al., 2015). For these work-processes to be competitive by improving plant utilisation, this study proposes that [A] big data are used to source [B] consumer preferences for [C] product development. The output of [C] product development feed into the design of the manufacturing equipment and plant, [D] conversion of preferences to process parameters [E] mass customisation. Through [G] maximised plant utilisation, the operation of competitive manufacturing and distribution processes are achieved through [F] flexible manufacturing systems.

The following works present evidence of the growing interest in big data on the supply chain and how big data carries potential value for improving the overall supply chain performance. Rozados and Tjahjono (2014), in their systematic literature review and case study analysis, looked at big data analytics in supply chain management. More recently, Nguyen et al. (2018) provided a framework that maps the use of big data analytics in supply chain management based on the latest research developments. Tiwari, Wee and Daryanto (2018) provide evidence on how consumer behaviour data provide further insights into the various aspects of the supply chain. These works attest ICT advances can integrate supply chain sub-processes to realise efficiency gains that can improve overall supply chain performance.

Next, the generation and application of big data on the various aspects of the supply chain are discussed.

2.3 Product Design, Product Lifecycle Management and Supply Chain [C] Product Development, [D] Conversion of Preferences to Process Parameters, [E] Mass Customisation, [F] Flexible Manufacturing Systems

In the previous section, literature pertaining to the sources and use of [A] big data in the SC and PLM work-processes are considered. This section discusses the links between the [C] product development construct and the SC and PLM work processes. As outlined and discussed in Chapter 1, this research is positioned at the interception of product development with supply chain and product lifecycle management work-processes. The literature consulted for this study presents evidence of this noteworthy interception in product design with the supply chain and product lifecycle management work-processes. This intercept is amplified in the definitions tendered for PLM (refer to Section 2.1.1) and supply chain (refer to Section

1.1) by du Preez et al. (2015) and Melnyk et al. (2009); respectively. Subsequent evidence on this intersection suggests it applies particularly to the [C] product development, PLM, and supply chain work-processes constructs and (or) associated functionalities. Since the intercepts between these work processes are significant, it follows that the application of market preference analytics in [C] product development will affect the supply chain (and PLM) and vice versa. The significant intercepts are brought to the fore in the literature reviewed in this section.

2.3.1 Trends in the Research Methods on PLM and Supply Chain Theory

A key observation by Pashaei and Olhager (2015) is that since the year 2000, there has been a steady growth in the number of publications concerning product architecture and the supply chain. Furthermore, they submit the visible positive trend dates back from 1995, alongside varying evident patterns of research methodologies that appear over time (Pashaei & Olhager, 2015). Lastly, Pashaei and Olhager (2015) point out that while case studies, conceptual modelling and mathematical modelling show stable performance. An immense contribution to the increase in publications is due to an increase in surveys since 2007 (Pashaei & Olhager, 2015). Thus, this study contributes to the conceptual modelling research body of knowledge.

2.3.2 Opportunities in PLM and Supply Chain for competitive advantage

In this section, the constructs of [B] consumer preferences; [C] product development together with the supply chain as it pertains to [E] mass customisation; [F] flexible manufacturing system and [G] plant utilisation; are discussed.

Labbi, Ouzizi and Douimi (2015) propose that supply chain constraints be integrated into the product design phase. Furthermore, that product specifications are factored in designing the supply chain. Nepal et al. (2012) note it is important to link product design in [C] product development and the supply chain, ([E] mass customisation, [F] flexible manufacturing systems & [G] plant utilisation) decisions at the front-end of product development. Thereby translate product attributes to process and performance requirements early in the [C] product development process. Simultaneously, influence supply chain design resulting in an improved supply chain configuration. The resulting improved supply chain configuration, created by linking product attributes and supply chain structures, leads to more refined customer satisfiers. Thereby further contributing to the competitive advantage. Moreover, the refined customer satisfiers can lead to higher product orders. This will increase a plant's utilisation.

The proposed conceptual framework for this study aligns with this view. It proposes that both [B] consumer preferences, which inform the product specifications in [C] product development phase, feed into the [E] mass customisation design. Khan et al.'s (2012) view aligns with that of Labbi, Ouzizi and Douimi (2015) and Nepal et al. (2012). Further, Khan et al. (2012) posit that competitive advantage and supply chain resilience (SCR) are achieved by aligning product design, during [C] product development, with the supply chain, i.e. in line with the presented framework: [E] mass customisation and leading to the deployment of [F] flexible manufacturing systems.

Ponomarov and Holcomb (2009: 131) define supply chain resilience as, “the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function.” From Khan et al.’s (2012) view, the proposed links in constructs [A] big data through to [F] flexible manufacturing systems of the model are pivotal for competitive advantage and supply chain resilience. The requirement this view presents is attainable through the identified links in the proposed framework.

Furthermore, Khan et al.’s (2012) view is supported by Novak and Eppinger's work (2001). Novak and Eppinger’s (2001) findings suggest that linking product attributes (which are obtained from [B] consumer preferences and finalised during the [C] product development’s design phase) with the supply chain structure, [E] mass customisation, and [F] flexible manufacturing systems, can lead to unique value through maximised [G] plant utilisation and competitive advantage.

According to Awaysheh and Klassen (2010), a firm's supply chain structure (SCS) concerns its dependency, distance, and transparency shared with its suppliers. Awaysheh and Klassen (2010) describe the dimensions inherent to defining a supply chain structure, as discussed next. Dependency relates to the degree to which a manufacturer depends on suppliers for critical resources, parts, or capabilities. While distance relates to the geographical, cultural and organisational distance of the suppliers. Distance affects the interaction between a manufacturer and its suppliers. Lastly, transparency relates to the extent to and ease with which information sharing between a manufacturer and its suppliers happens (Awaysheh & Klassen, 2010).

Novak and Eppinger (2001) explored the relationship between product attributes, from [B] consumer preferences and [C] product development, and the vertical integration of supply chain, [E] mass customisation and [F] flexible manufacturing systems performance (SCP). Novak and Eppinger (2001) found firms that optimise product architectures together with SCC perform better than those focusing on improving either product attributes or SCC. Product architectures are determined during the [C] product development construct's design phase. At the same time, supply chain capabilities are captured in the constructs of [E] mass customisation and [F] flexible manufacturing systems (SCC). Irfan et al. (2019: 116), drawing from works by Wu et al. (2006) and Braunscheidel and Suresh (2009), describe SCC as: "the capability to use internal and external resources to coordinate the supply chain and daily operational activities." SCC is a firm's coordination and execution of its operational functions to respond to market dynamics (Irfan, Wang & Akhtar, 2019). The deployment of [F] flexible manufacturing systems is the means through which the dynamic capacity requirements can be met.

From the research mentioned above, it is apparent an opportunity exists for manufacturers to improve plant utilisation within the supply chain. This opportunity links big data to the PLM and SC work processes. Thus, it links to the supply chain's capabilities, performance, structure, and resilience. Moreover, using market preference analytics with equipment management data can unearth and contribute invaluable business intelligence to the manufacturer. This intelligence can improve the manufacturer's product architecture, SCS, SCC, SCR, SCP operation, and design optimisation activities. These discrete elements, i.e. product architecture, SCS, SCC, SCR and SCP, can be optimised independently or in various combinations to get the desired improved performance as suggested by Novak and Eppinger (2001). By linking big data to the respective work processes, value can be created for both the consumers and manufacturers. This value can lead to a manufacturer's new strategic positions resulting in competitive advantages.

2.4 Mass Customisation for [F] Flexible Manufacturing Systems

In this section, the literature on how [E] mass customisation relates to [F] flexible manufacturing system and [G] plant utilisation is considered.

[E] mass customisation (MC) and (or) privatisation can, in no small extent, enable manufacturers to exploit the positions Porter (1996) elucidates (refer to Section 1.1). This MC can be enabled by combining the voice of the consumer (VOC) (in the form of market preference analytics) in the design processes required for both PLM and the supply chain. As discussed in Chapter 1, the VOC is captured using market preference analytics in the proposed framework. Furthermore, the use of market preference analytics fulfils the requirements of the process of value co-creation in MC to a large extent. Thus, it attains realising the strategic positions that lead to total value for both the consumer and the manufacturer. Simultaneously, MC enables Labbi, Ouzizi and Douimi's (2015) proposal (refer to Section 2.2.2) to integrate supply chain constraints into PLM and vice versa.

The manufacturer and the consumer's value drivers have been considered for MC in the literature (Fogliatto, da Silveira & Borenstein, 2012). Merle, Chandon and Roux (2008) present two elements that are perceived as customer value viz.:

(i) product value which has three further dimensions: utilitarian, individuality and self-expression with

(ii) experiential co-design value presenting two dimensions: hedonic and creative freedom.

Manufacturers' value realisation is defined by Piller et al. (2004) as primarily the difference between the prices for customised products and the cost of customisation. Secondarily, "economies of integration" are a result of the postponement of differentiation activities. Lastly, improved market information and consumer loyalty are considered. Bharadwaj et al. (2009) elaborate on customer loyalty by suggesting that consumer retention and repeat business in mass customisation are a function of consumer confidence in their unique preferences.

Typically, the lack of involvement from the necessary stakeholders leads to unnecessary changes. These unnecessary changes can emanate from product design up to and including supply chain structures. In their study, Zheng et al. (2017) reaffirmed user experience as a key design input in product development and subsequent success. Moreover, Zheng et al. (2017) recommend that the following considerations be taken prior to implementation:

(i) upfront cost plan,
(ii) the complexity of the product and
(iii) the design of human participation studies.

Furthermore, their research suggests specific data-driven design methods should be developed to analyse multi-user generated big data (Zheng et al., 2017). Further, Zheng et al. (2017) suggest the data-driven design method should aim to actively maximise human participation through the traditional methods of sourcing consumer preferences that include focus groups and surveys. This research suggests this is to be done simultaneously, with the sourcing of passively generated data. The data is to be extracted from ICT platforms, including social media platforms, to leverage the opportunity to extract customer requirements. Thereon, create product architecture that meets the constraint of reduced downstream supply chain complexity, maximised utilisation. Thus, the inherently reduced cost to maximise value for both manufacturers and consumers.

The [E] mass customisation construct has been included in the model because it increases the plant equipment's utilisation to raise [G] plant utilisation. [E] MC is, at present, the only manufacturing model that accommodates market preference analytics. This accommodation is achieved with positive offshoots that lead to competitive advantages. These competitive advantages are a result of co-creation. The models of value co-creation are discussed in the following section.

2.4.1 Co-creation in Product Design for Mass Customisation

Two dominant models for co-creation are found in literature viz. a) online-configuration (Salvador & Forza, 2004) and b) embedded toolkits for user co-creation (Piller, Ihl & Steiner, 2010). These models present the opportunity to facilitate market preference-based analytics interfacing with PLM and SC's downstream processes. Mainly analytics that have been sourced from consumer opinion and product use, i.e., consumer behaviour data. These are the models that are referred to as [E] mass customisation in the proposed framework. These models can be used to design and optimise the equipment for [F] flexible manufacturing systems proposed in the framework. These models are discussed in the following sub-section:

Online-configuration:

According to Wang and Tseng (2011), an online configuration comprises pre-defined attributes with rules to guide consumer product attribute selection. Consumer requirements are captured into a system that converts the consumer requirements into preselected product attributes (Wang & Tseng, 2011). Wang and Tseng (2011) point out this model's shortfall is in that it limits the possible product attribute combinations to those within the predefined characteristics range. Consequently, reducing variants could achieve greater consumer satisfaction as the consumer is often “forced to settle” (Wang & Tseng, 2011). Furthermore, alterations that are later made in the product creation process can require capital expenditure that needs to be justified. Thus, the real opportunity in co-creation lies in maximising the user’s quality requirements. This study postulates the user’s requirements are available through market preference analytics extracted from big data and can be used to predefine these attributes.

However, this model does not entirely accommodate the dynamism inherent to consumer preferences (Li et al., 2015). Consumer preferences are rarely constant. This inability to accommodate the dynamic changes in preferences means the value in market preference analytics is not fully realised.

In addition to the limitations imposed by the online configuration model, Nepal, Monplaisir, and Famuyiwa (2012) highlight that existing supply chains impose constraints on product architecture. Consequently, this confines the user personal design experience (Nepal, Monplaisir & Famuyiwa, 2012).

Embedded toolkits

A more accommodating co-creation model is the embedded toolkit. Embedded toolkits for user co-creation, also known as the postponement method, are used to increase design flexibility (Zhang, Ren, Liu, Sakao, et al., 2017). Products are designed with built-in flexibility by allowing some product specifications into the user's domain (Zheng et al., 2017). Gross and Antons (2009) recommend a model should include 1) a flexible architecture with adaptable design parameters, 2) a set of guidelines to ascertain the viability of possible configurations, and 3) an interface that allows users to input variables aligned to their individual preferences. While this approach captures the consumer sentiment, the resulting product architecture can be as varied as consumers; thus, dictating highly complex manufacturing systems and subsequent processes.

In the next section, the use of [F] FMS, and the benefits, to resolve the complexities that [E] mass customisation introduces to the SC and PLM work-processes are discussed.

2.5 [F] Flexible Manufacturing Systems and [G] Plant Utilisation

Al-Kahtani et al. (2014), in their simulation-based study, suggest the complexity that is needed to fulfil [E] mass customisation requirements can be handled by [F] flexible manufacturing systems. Shafiq, Faheem and Ali’s (2010) posit this is enabled by the flexibility types that can be derived for [F] FMS. These flexibility types include product flexibility, process flexibility, operation flexibility, expansion flexibility and production flexibility. This view is supported by El-Tamimi et al. (2012) and Mahmood et al. (2017), both of whom have conducted performance analyses of an FMS using process modelling and simulation methodologies. Al-Kahtani et al. (2014), in the same work, propose [F] flexible manufacturing systems installations have yielded improvement in capital utilisation; thus, [G] plant utilisation, increased profit margins and competitive advantage are apparent.

Wiendahl et al. (2007) state that a complex manufacturing system's design and engineering analysis is a challenging exercise. Wiendahl et al. (2007) point out that its operation is made even more challenging when flexibility and reconfigurability parameters are incorporated. Various researchers have looked at flexible manufacturing systems' operation to maximise machine and overall utilisation ([G] plant utilisation). Literature provides evidence of many case studies that incorporate FMS simulation techniques with improved overall utilisation and production rate, *inter alia* by redesign.

This body of work includes that of Shafiq, Faheem and Ali (2010), who present a framework to determine the effect of scheduling and manufacturing flexibility on the performance of [F] flexible manufacturing system. Shafiq, Faheem and Ali's (2010) investigation considered system configuration; manufacturing (routing) flexibility; the number of pallets; the volume of parts produced; scheduling as it applies to dispatching and sequencing rules and buffer capacity. The findings from Shafiq, Faheem and Ali's (2010) investigation were: a decrease in the time to complete a job (make span); reduced work in progress; an increase in the machine utilisation (which is directly linked to [G] plant utilisation) and production cost with increase in the routing flexibility.

Work presented by Singholi et al. (2010) of a case study to analyse a plant that manufactures valves and employs [F] flexible manufacturing systems; considering performance parameters viz. production rate, makes span time and overall utilisation ([G] plant utilisation). The same study considers these operational performance parameters after improving the [F] flexible manufacturing system design. Singholi et al.'s (2010) yielded higher overall utilisation of resources ([G] plant utilisation) and maximum throughputs. Ali, Qureshi and Jahanzaib (2013) conducted a performance improvement study on a [F] flexible manufacturing system for a compressed natural gas (CNG) equipment electrical control device manufacturing plant. Their research indicated that by restructuring and redesigning, i.e. reconfiguring the manufacturing system to enable flexible manufacturing, machine utilisation could be improved (Ali, Qureshi & Jahanzaib, 2013). Additionally, Ali, Qureshi, and Jahanzaib (2013) found that modifying and sizing the FMS resulted in higher production throughputs.

However, Yildirim, and Yücel (2016), who conducted an experimental investigation on micro-FMS, argue FMS can never be fully flexible; thus, they are limited to a range of parts or products they can produce. Further, Yildirim and Yücel (2016) point out that FMS's capability is limited to a single product family or a limited range of products; these are mutually exclusive. Even with this limitation, the reviewed literature presents an overview that these [F] flexible manufacturing systems are instrumental and are more promising than traditional mass production systems in attaining the goal of maximising plant utilisation and increasing production throughput rates.

2.6 Conclusion of Literature Review and Hypotheses

The research evidence presented here is not exhaustive; however, it provides a high-level view of the contribution made to this field. From this literature survey, a gap in the research of the use of market preference data in the design and operation of supply chain and product lifecycle management is identified. This gap is further widened by product development treatment as a distinct process from the SC and PLM work processes. This treatment pervades even though product development is a process step within both SC and PLM work processes.

As seen in the literature, sources of big data are varied and valuable. In the form of market preference analytics, big data's integration into the design and operation supply chain can overcome the throughput constraints, leading to maximised plant utilised plant utilisation by using flexible manufacturing systems.

Figure 1.2 depicts the hypotheses:

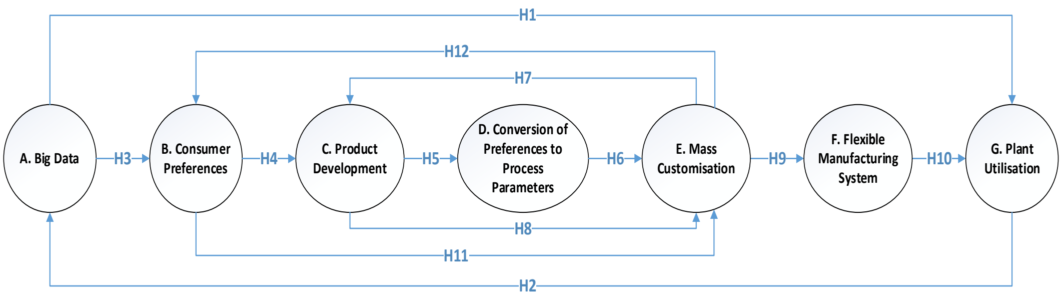

Figure 1.2: Conceptual framework on the use of big data for product development in mass customisation

From the preceding literature, the following hypotheses are formed:

Hypothesis 1 (H1) and Hypothesis 2 (H2): Big data is positively related to plant utilisation.

Hypothesis 3 (H3): Big data is positively related to consumer preferences.

Hypothesis 4 (H4): Consumer preference data are positively related to product development.

Hypothesis 5 (H5): Product development is positively related to process parameters in manufacturing.

Hypothesis 6 (H6): Process parameters are positively related to mass customisation in terms of the manufacturing equipment design and optimisation.

Hypothesis 7 (H7) and Hypothesis 8 (H8): Product development is related to mass customisation (in terms of the manufacturing equipment design and optimisation).

Hypothesis 9 (H9): Mass customisation (equipment design, including its optimisation) are positively related to flexible manufacturing systems.

Hypothesis 10 (H10): Flexible manufacturing systems are positively related to plant utilisation

Hypothesis 11 (H11) and Hypothesis 12 (H12): Consumer preferences are related to mass customisation in terms of the manufacturing equipment design and optimisation.

Next, the research paradigm and methodology that are adopted for this research are discussed.

CHAPTER 3: RESEARCH METHOD

3.1 Introduction

This section elaborates on the research methodology/paradigm (refer to section 3.1) adopted in this research. This is followed by a description of the research design (refer to section 3.2). The overview of the Delphi Technique is then presented (refer to section 3.3). Following this is the discussion of the panel selection (refer to section 3.4). The research instrument is then discussed (refer to section 3.5). Thereafter, data analysis and interpretation are considered (refer to section 3.6). The issues of validity and reliability are then discussed. The section is closed with a discussion on ethics (refer to section 3.7).

3.2 Research Methodology/Paradigm

This research uses exploratory sequential mixed methods. According to Creswell (2014), exploratory sequential mixed methods refer to using an initial qualitative (open-ended questions) research phase to explore the panellists' views. This is then followed by a quantitative (closed-ended questions) research phase. For the latter phase, the initial phase's data is analysed and built into the qualitative phase (Creswell, 2014; Leedy & Ormrod, 2015). In addition, both works by Leedy and Ormrod (2015) and Creswell (2014) point out the database generated from the second round builds onto the first database. The research paradigm is discussed next.

Meredith et al. (1989) discuss the two different dimensions of research for operations research viz.:

(a) “rational/existential dimension” is based on the nature of truth. It assesses the extent of its logic and the degree of its independence from human influence or whether it is an experiential phenomenon, one that is explained through individual experience. It concerns the epistemological structure of the investigation process itself. It encompasses two polarities: rationalism as one pole, which measures truth using formal structure, and pure logic, thus conforms to a deductive approach. With existentialism as the opposite pole that builds on the tenet, knowledge is constructed through an individual's correspondence with their environment and conforms to an inductive approach (Meredith et al., 1989). The latter dimension is more applicable to the present study. This study explores the future possible application and interaction of technological advancements to be used by individuals or groups. The study enquires the application of big data in the product development work process for FMS design and operations.

Within this dimension, the degree of formalism is graded into the following perspectives:

(i) the *axiomatic,* which concerns a theorem-proof world or research.

(ii) the *logical positivist/empiricist,* which assumes the phenomenon being considered is independent of the environment in which it occurs.

(iii) the i*nterpretive perspective* does not separate the phenomenon from its environment and focuses on meanings rather than behaviour. According to Bhattacherjee (2012), it is based on the tenet that social reality is not objective but it is instead shaped by the experience and contexts of society (ontology). They recommend since social reality is not singular, it should be studied within its socio-historic context by consolidating the participants' subjective interpretations (epistemology).

(iv) the *critical theory perspective:* creates a synthesis of the positivist and interpretivist perspectives. It positions knowledge in the broad application of its role in social evolutions.

Since this study's focus is on work-processes, this necessitates attention is paid to the interaction of big data and the context of use. In this research, the context is product development for flexible manufacturing systems to maximise plant utilisation, lending this research to an interpretive study.

(b) “natural/artificial” deals with the source and the nature of the information used in the investigation. The natural pole of this dimension is empiricism, with the opposite pole of subjectivism. In this dimension, three mechanisms are used to form the researcher’s perception:

(i) *object reality* which requires the researcher to directly observe the phenomenon with the assumption that the human senses can detect the characteristics of objective reality and corresponds to empiricism;

(ii) *people’s perceptions of object reality,* the researcher relies on the perceptions or abstract representation of the reality of the people who are exposed to the phenomenon;

(iii) *artificial reconstruction of object reality* recasts the objective reality from any of the preceding mechanisms. It is subject to the researcher's discretion regarding their understanding concerning the object reality (Meredith et al., 1989).

This study followed (ii) people’s perception of the object reality method of research to elicit information about the current state. This method led to the use of multiple perceptions to understand the current state. Simultaneously, drawing from the participants' expertise and experience to determine possible present and future configurations of the work process of interest. This approach inherently achieves triangulation (Meredith et al., 1989).

Meredith et al. (1989) offer the plot, as shown in Figure 3.1, which lists the research instruments as they correspond to the dimensions discussed above.

		Natural		Artificial
Rational		Direct observation of object reality	People's perceptions of object reality	Artificial reconstruction of object reality
	Axiomatic			Reason/Logic/Theorems Normative Modeling Descriptive Modeling
	Logical Positivist/ Empiricist	Field Studies Field Experiments	Structured Interviewing Survey Research	Prototyping Physical Modeling Laboratory Experimentation Simulation
	Interpretive	Action Research Case Studies	Historical Analysis Delphi Intensive Interviewing Expert Panels Future/Scenarios	Conceptual Modeling Hermeneutics
Existential	Critical Theory		Introspective Reflection	

Figure 3.1: Framework for research methods (adapted from Meredith et al. (1989))

For this research, the case study, which is interpretive and makes use of direct observation dimensions; and simulation research, which is logical positivist and is the artificial reconstruction of objective dimensions, methodologies were considered (Meredith et al., 1989). However, these are not viable options due to the study's objectives, which seek to assess the feasibility of creating a framework for a work process that is not known to be used. This factor, coupled with the amount of data required for the requisite rigour to generate sufficiently comprehensive tools for future use and broad application, renders the two methods superfluous. Instead, the Delphi Technique, located at the interception of *interpretive perspective* and *people's perceptions of object reality* research mechanism (Meredith et al., 1989), is better suited for this study.

Creswell (2014) describes paradigms as the general philosophical disposition about the world and the research's nature which contributes to the study. Creswell (2014) typifies the main philosophical inclinations to include: positivism, constructivism, transformative, and pragmatism. Table 3.1 summarises the main elements of these different worldviews:

Table 3.1: Four Paradigms and the elements (adapted from (Creswell, 2014))

Postpositivism	Constructivism
Determination Reductionism Empirical observation and measurement Theory verification	Understanding Multiple participant meanings Social and historical construction Theory generation
Transformative	**Pragmatism**
Political Power and justice oriented Collaborative Change-oriented	Consequences of actions Problem-centred Pluralistic Real-world practice oriented

The characterisation offered by Creswell (2014) intersects with the discussion offered by Meredith et al. (1989) at the pragmatism worldview. According to Creswell (2014), pragmatism does not hinge on one system of philosophy and reality. It applies multiple methods for collecting and analysing data. It sees truth as what applies at the time of inquiry. It is not grounded on reality's dual nature, i.e. reality independent of the mind or within the mind. Pragmatism considers the "what" and "how" approach to the research based on the research's direction and intended outcomes. This worldview always considers the context in which the research is undertaken

(Creswell, 2014). These considerations align with the objectives of this study.

3.3 Research Design

This study's hypotheses as well as subsequent reliability and ecological validity, are adequately tested using an exploratory sequential mixed methods design. This research design is conducted by collecting primary data from a cross-sectional qualitative survey, followed by a cross-sectional quantitative survey, as summarised in Figure 3.2 (Creswell, 2014; Leedy & Ormrod, 2015).

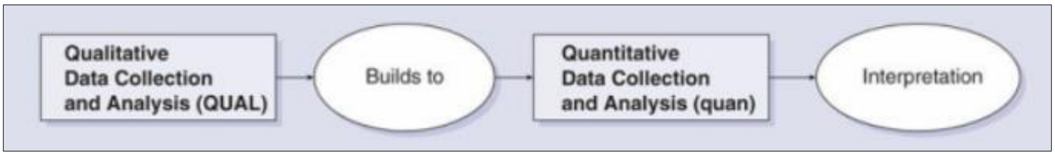

Figure 3.2: Exploratory Sequential Mixed Methods Strategy. Source: Leedy and Ormrod (2015: 270)

Leedy and Ormrod (2015) state that qualitative research typically focuses on:

(i) current or historical phenomena as they occur(ed) in their natural setting - in the "real-world" and

(ii) capturing and studying the complexity of the relevant phenomena (Bhattacherjee, 2012).

Further, Leedy and Ormrod (2015) motivate that qualitative research is best suited for instances wherein: information on topics is sparse; involved variables are not known; and theory base is lacking. Bhattacherjee (2012) supports this view by Leedy and Ormrod (2015), further adding that qualitative research relies on the researcher’s skills to analyse and integrate as well as their knowledge of the context of data collection. Qualitative research is appropriate for this study because it investigates a conceptual framework based on constructs and novel associations. Creswell (2014) describes qualitative research as depending on text and image data coupled with unique steps for data analysis and presenting a wide diversity of designs. Expert opinion on the proposed conceptual framework is sought and obtained in text form. This enquiry thus makes qualitative best suited for the initial round of the study.

Quantitative research occurs in two forms, viz. descriptive and inferential statistics (Bhattacherjee, 2012; Leedy & Ormrod, 2015). The descriptive analysis applies statistical description, aggregation and presentation of the investigated constructs and (or) linkages between them (Bhattacherjee, 2012). Whereas “inferential analysis refers to statistical testing of hypotheses (theory testing)” (Bhattacherjee, 2012: 119). Both forms of quantitative research are appropriate for this study. The investigated conceptual framework’s constructs are analysed using both descriptive and inferential quantitative forms. Leedy and Ormrod (2015) state that descriptive quantitative research identifies a phenomenon's characteristics or explores relationships among phenomena (Leedy & Ormrod, 2015). Bhattacherjee (2012) notes that quantitative research is statistics-driven and has a low reliance on the researcher. The properties of quantitative and qualitative research are shown in Figure 3.3.

Research Aspect	Qualitative	Quantitative
Research Focus	Understand and interpret	Describe, explain, predict
Researcher Involvement	High	Limited/controlled
Research Purpose	Theory building	Theory testing
Sample Design	Non-probability	Probability
Sample Size	Small	Large
Research Design	May change during course of study Generally uses more than one method Consistency is not anticipated Longitudinal approach	Identified before study is initiated Uses single or mixed methods Consistency is important Cross-sectional or longitudinal approach
Participant Preparation	Generally involves pre-tasking	No preparation - avoid bias
Data Type and Preparation	Verbal or visual descriptions Converted to verbal codes Computer analysis sometimes used	Verbal descriptions Converted to numerical codes Computer analysis required
Data Analysis	Human analysis after coding Mainly non-quantitative Researcher forced to view contextual framework Unclear distinction between facts and judgements Ongoing throughout study	Computer analysis Predominantly statistical and mathematical methods Clear distinction between facts and judgements Potentially ongoing
Insights and Meaning	Deeper level understandings Researcher insights formed and tested during process	Limited probing and quality of data Insights follow data entry
Research Sponsor Involvement	Potential observers	Generally no contact
Feedback Turnaround	Smaller sample can result in faster and shorter data collection Shorter data analysis from insights formed throughout study	Large sample creates longer data collection times Insight development occurs after data collection creating a longer process
Data Security	Strong from restricted access and smaller sample sizes	Generally, competitors become aware of research from which insights can be leaked

Figure 3.3: Properties of Qualitative and Quantitative Research. Source: Cooper & Schindler (2014: 147)

The cross-sectional method allows for collecting data to be carried out at one point in time (Creswell, 2014; Leedy & Ormrod, 2015). This design is in accordance with the Delphi Technique (Akkermans et al., 2003; Powell, 2003; Yousuf, 2007; Melnyk et al., 2009; Hsu & Sandford, 2015). This research is based on a non-experimental design because it does not make use of random assignments and treatment manipulation (Bhattacherjee, 2012). This method is consistent with the research paradigm's intent that the knowledge takes the form of pragmatism. Moreover, it aligns with the mixed-methods research strategy (Creswell, 2014; Leedy & Ormrod, 2015).

The sequential exploratory mixed-methods data collection is conducted as per the dictates of the Delphi Technique. For this study, this means that the data collection is carried out over two successive rounds. Checklists, rating scales, and rubrics are the three techniques used to facilitate the quantifying of complex phenomena (Leedy & Ormrod, 2015). Researchers use checklists to identify behaviours or characteristics that are observed, present, real or otherwise. Rating scales/Likert scales are used to evaluate behaviour, attitude or another phenomenon of interest over a continuum. Rubrics improve on rating scales and are useful to aid a researcher’s evaluation. Typically, rubrics contain two or more rating scales that evaluate different aspects of participants’ performance with definite descriptions of how performance manifests itself along each scale (Leedy & Ormrod, 2015).

Following the Delphi Technique, as administered in a study by Melnyk et al. (2009), a rating scale using the Likert-type scale non-experimental questionnaire is developed from the literature survey for the initial round. This questionnaire is open-ended, allowing panellists the opportunity to comment on the issues identified from the literature and raise issues they deem should be considered in the study. For the final round, the initial questionnaire was modified to include issues identified by the panellist in the initial round. Both the questions from the initial questionnaire and the issues raised by the panellists are presented as closed-ended Likert-type scale questions.

The questionnaires were loaded and administered online using Google Forms. Google Forms as a platform allowed for creating private Google accounts shared exclusively with the panellists. Using Google Forms allowed the surveys to be accessible only to the specific panellists who were associated with the Google accounts. This exclusive access was generated by creating Google accounts and randomly creating login names and passwords for the panellists. For every round, these login details and the individual round instructions were sent to the panellists. This targeted and controlled access ensured accurate collection and tracing of the panellists' responses between the successive rounds. This control further ensured each panellist's ratings could be presented to them in the final round.

Additionally, Google Forms proves an efficient method for data collection vis-à-vis the use of paper-based data collection. Moreover, this online platform encourages panellists to share their views at their own pace, anonymously. Moreover, the use of Google Forms to administer the surveys made conforming to the University of the Witwatersrand's Ethics Protocol effective and efficient (refer to **Appendix A** for Ethics Clearance Form). This conformance kept the research procedure to a minimum risk rating.

3.4 Overview of the Delphi Technique

The Delphi Technique was originally developed in the 1950s by Dalkey and Helmer at the Rand Corporation (Turoff, 1970; Schmidt, 1997; Turoff & Linstone, 2002; Akkermans et al., 2003; Meredith, 2009; Baines & Shi, 2015). The technique has gained popularity as a research method and has been used in over 1000 cases as it allows for the exchange of ideas among large groups who otherwise would ordinarily be constrained by geographies (Turoff, 1970; Schmidt, 1997; Turoff & Linstone, 2002; Akkermans et al., 2003; Meredith, 2009; Baines & Shi, 2015). Turoff and Linstone (2002) advise the method is applicable in a problem that does not advance to 'precise analytical techniques' but would instead be aided by collective subjective judgement.

In this research, collective subjective judgment is solicited from expert opinion. The opinions sought are on how consumer preferences mined from big data may be used to design and operate FMS to improve plant utilisation. This opinion elicitation approach is in accordance with Loughlin and Moore (1979), who state that the Delphi Technique is a systematic tool for eliciting opinions from individual experts on a subject within the realm of their expertise. Additional justification of the method's appropriateness for this type of study is given by Chocholik et al. (1999) and Meredith et al. (1989). Chocholik et al. (1999) and Meredith et al. (1989) recommend the Delphi technique as a type of expert panel technique developed to forecast possible alternative scenarios and for exploratory research (Meredith et al., 1989; Akkermans et al., 2003; Hsu & Sandford, 2015). Although the Delphi Technique is popular for forecasting, Turoff and Linstone (2002) add that the technique is equally useful in generating the structure of a model. Further, the evidence presented by Meredith et al. (1989) and Habibi, Sarafrazi and Izadyar (2014) shows the technique's usefulness extends from exploratory research to include identifying the basic elements of a phenomenon. Exploratory research design is suited to (i) determine the scope of a phenomenon, behaviour, or problem; (ii) derive ideas on the phenomenon and; (iii) evaluate the feasibility of an effort prior to a more in-depth study on the phenomenon (Bhattacherjee, 2012).

The Delphi Technique is appropriate for this study. This study seeks to determine a possible configuration of the supply chain and product lifecycle management work-processes. In this study, the technique is used to elicit individual opinions from experts across disciplines, primarily within the FMCG industry, industries similar to FMCG, i.e., pharmaceuticals industries and ICT industries. The collected opinions are then combined to arrive at an informed consolidated outcome.

This study is exploratory. It enquires about a conceptual framework for a work-process that links big data to maximised plant utilisation through FMS's design and operation.

3.5 Panel Selection

3.5.1 Defining an Expert: Panel Attributes

A purposive sampling approach is used. This non-probability approach gives the researcher scope to use judgment to select according to the required perspectives (Leedy & Ormrod, 2015). The search for, identification and selection criteria for experts to form the panel was based on the following literature assessment. Work done by Bolger and Wright (1994) to assess the veracity of expert opinion found common practice attributes expertise on social standing and believability. Bolger and Wright (1994), drawing from work by Johnson (1983), suggest that experts are people perceived to:

(i) be well taught
(ii) have attained a certain level of skill, acquired through practice, that leads to dextrous execution
(iii) possess a significant amount of body of knowledge
(iv) have developed discipline-specific sense to have heuristics for real-world application of their knowledge
(v) demonstrate a level of general problem-solving skills, including the ability to separate out superfluous detail from the relevant information required in solving familiar problems.

Shanteau (1988) identified the social traits of experts:

(i) Effective communication skills
(ii) Owning up to the consequences of their decisions
(iii) Assurance in decisions
(iv) High levels of stress tolerance

Despite the stated characteristics, Bolger and Wright (1994) highlight the shortcomings of definitions that are arrived at using competence models to define professionalism and expertise. They argue that the models-based definitions obstruct the empirical data that the same attempt to substantiate (Bolger & Wright, 1994). Bolger and Wright (1994) also argue that the focus for the present should be on data collection regarding expert performance, which should be considered the distinctive determining characteristic. Furthermore, Bolger and Wright (1994) propose expertise should be defined based on the higher performance demonstrated by these systems or people vis-a-vis people or systems otherwise designated. Bolger and Wright (1994) further separate substantive experts, i.e. skilled data analysts, from assessment experts, i.e. decision-makers in uncertainty.

For this study, both types of experts were consulted primarily to build credence to the discrete constructs and linkages proposed in the conceptual framework. Secondarily, to share knowledge across disciplines and viewpoints among the two types of experts to arrive at a well-interrogated and well-informed convergence of opinion. This study approached these outcomes by ensuring the Delphi Technique's implementation enabled capturing the best available opinion. The best available opinion is elicited in this manner: for subsequent Delphi study rounds to be initiated, summarised feedback from the initial round was shared with the panellists. Consequently, this leads to a synthesis of an opinion based on substantive and assessment judgements. Bolger and Wright (1994) conclude judgmental performance is dependent on two factors: ecological validity and learn-ability.

Table 3.2 summarises the theory supporting attributes from various scholars. The information in Table 3.2 is compiled from work by Goodman (1987); Shanteau (1988); Bolger and Wright (1994); Shanteau et al. (2001), (2002a) and Baker, Lovell, and Harris (2006).

Shanteau et al. (2002b) further propose the use of Cochran-Weiss-Shanteau (CWS), which is a ratio of discrimination to inconsistency. Discrimination refers to the ability to distinguish the detail from the valuable information; and the ability to discern the difference between similar but not identical situations—this characteristic, coupled with the internal consistency criterion as previously described.

Table 3.2: Expert Attributes by scholars.

Attribute	Description	Short-coming	Contributing Author(s)
Experience	The duration spent on the job. It is measured by the time duration threshold of working within a specific discipline or field and the ability to influence policy. These characteristics are linked to seniority and (or) the weight an organisation carries in driving decision-making, especially as it relates to national regulation	No correlation exists with accuracy and experience, except for that more experienced individuals exude more confidence.	Goldberg (1968), Bolger and Wright (1994), Shanteu (2001) and Baker, Lovell, and Harris (2006)
Accreditation	Refers to accreditation given by a professional body as a reflection of expertise. Certified people have a higher likelihood of being experts versus people without certification.	Accreditations are tied to the job and not to the performance. These accreditations are typically held for life despite the reality that skill level declines over time.	Shanteau et al. (2003)
Social acclamation (Subject Matter Experts)	Refers to common recognition from professionals in a field—subject matter experts',i.e. professionals who work in the field., recommendations.	The shortcoming of this approach is that it can be popularity-based. Meaning that people outside the consulted professionals' sphere of operation are not considered. They may be great performers but may not	Phelps(1977), Nagy (1981), Milton (1994), Shanteau (2001), Mead and Moseley (2001),

		be popular among the approached referees.	
Consensus	Refers to reliability viewed as agreement amongst individuals as necessary amongst experts	This view carries risks, including groupthink. Additionally, this approach fails when considering different schools of thought as it applies to decision-making. Internal consistency within one school can be high; however, it manifests sizable disagreements amongst scholars from different schools.	Slovic (1969), Einhorn (1972), Janus (1972), Ashton (1985), Milton(1994), Stewart et al. (1997), Shanteau (2001)
Discrimination	Refers to the ability to discern at a more advanced level than a novice would. Thus, implying an expert would separate material attributes matter from those that are immaterial.	A novice may be able to apply a simple rule that is based on an easily perceptible but irrelevant characteristic, thus making them perform at the expert level.	Hammond (1996), Shanteau (1992), Shanteau (2001)
Consistency (internal) reliability	Refers to an individual's decision-making must be consistent over time.	Internal consistency as a superficial measure could lead to the misidentification of an expert. A person	Slovic (1969),Einhorn (1972), Einhorn (1974),

		who is not an expert could be misidentified as one.	Shanteau (1999), Stewart et al. (1997)
Behavioural characteristics	This construct refers to the fact that experts exhibit certain traits that can be set as a standard on an expert trait profile. Novices who aspire to the expert level could then be measured against the standard, which would be experts' scores.	This approach faces three hurdles: the required tests for the different characteristics; the normalisation of the test to fit the domain of interest; and the point of departure in so far as the degree to which novices may possess the pre-determined traits.	Shanteau et al. (2003)
Knowledge tests	This construct is based on the premise that domain-specific facts are requisite for expertise as this knowledge informs competent decisions. Moreover, the ability to discern the facts applicable to a given situation is the additional characteristic required of experts.	Registered qualifications are not consistent with expertise. For example, a registered nurse could not define research priorities but be able to identify functional areas of difficulties. Individuals can know issues without experience.	Chi (1978), Williams and Webb (1994), Hardy et al. (2004), Shanteau et al. (2003)
Creation of experts	Refers to the process whereby researchers give extensive training to impart a skill to novices.	Various disciplines require different durations for training and learning on expertise.	Shanteau (1988) and Shanteau et al. (2003)

Shanteau (1988), Bolger and Wright (1994), Shanteau et al. (2001), Shanteau et al.(2002b) and Baker, Lovell, and Harris (2006) appear to present diverging traits. Despite this, these researchers agree experts should have knowledge of and experience in their field. However, some workers argue experts do not necessarily have to be used for the Delphi Technique (Goodman, 1987; Baker, Lovell & Harris, 2006). Goodman (1987) and Baker, Lovell and Harris (2006) argue that informed advocates for a specific discipline or topic should be used. Submitting stringent definitions for an expert can breach the 'pragmatic' nature of a Delphi and thereby dramatically reduce the number of reachable available experts (Goodman, 1987; Baker, Lovell & Harris, 2006). Sahari et al. (2018) ascertain knowledge is the key criterion for an "expert" to be used in panel selection.

Baker, Lovell, and Harris (2006) point out knowledge is measured by professional qualification or professional registration. Experience is measured by a certain time duration of working within a specific discipline or field and influencing policy. It is linked to seniority and (or) the weight an organisation carries in driving decision-making, especially as it relates to national regulation (Baker, Lovell & Harris, 2006). For this study, both qualification (and certification where applicable) and experience were vital considerations to qualify for being an expert on the panel. These have been used as key criteria in the selection of the panellists.

Moreover, the rapid development in ICT and manufacturing-related infra-structure has introduced some unforeseen changes and (or) improvements in work processes and, in some instances, across disciplines. When considered, these changes necessitated panellists from across organisational levels be recruited for this study. This recruitment strategy captured the expertise heterogeneity that time and ICT developments have imposed on organisational work-processes. These work processes and expertise include tactical and strategic perspectives in a firm, with specific reference to how things would have been done before the work tools were implemented and knowledge improvements made. For example, a person who started in a role at a particular business ten (10) years ago would have completed a task differently from a person starting in a similar role today. This difference in approach would be a consequence of (i) learning the qualifications of an individual is in theory based on the best available information at the time it was granted; that as well as (ii) improvements in technologies, the working processes, and tools have advanced since an individual would have joined an organisation.

This panel selection strategy follows recommendations presented in works by Jairath and Weinstein (1994), Yousuf (2007), and Murphy et al. (1998). Jairath and Weinstein (1994) suggest the panel contribute the latest available knowledge and perceptions with objectivity on the study results. Yousuf (2007) stresses that often future developments in a field are not correctly predicted by experts but rather by amateur outsiders' unconventional thinking. Murphy et al. (1998) recommended that the panel participants' diversity creates different views and a more comprehensive range of possible solutions. By aligning the selection criteria to these works, the panel composition fulfils characteristics that align with the study objectives. This study’s objective to determine constructs for a work process framework; reliability hinges on in-depth experience, indicated by the number of years spent in a particular field. Simultaneously, the latest available tools and advances in disciplines are typically linked to the new entrants in the field.

3.5.2 Panel Size

Reid (1988) notes that panel size can be between ten (10) and 1658. Sahari et al. (2018) propose the study would include a minimum of seven (7) or eight (8) experts. A minimum of four (4) with a maximum of 3000 is not uncommon (Thangaratinam & Redman, 2005). This study purposed to recruit fifteen (15) expert participants. Forty-four (44) potential respondents were approached and invited via LinkedIn InMail, word of mouth referrals (including instant messaging) and emails. Twenty-three (23) experts agreed to participate. They were forwarded the Information Sheet, which included the Consent Form (refer to **Appendix B**). The consent form was mandatory for them to sign before commencing with round one (1). Round one (1) of the study had sixteen (16) participants subsequent round two (2) ended with thirteen (13) responses. In this instance, the research scope and the availability of resources determined the number of participants (Fink et al., 1984; Hasson, 2000).

3.6 Research Instrument

A set of questions based on the literature review were developed. Hasson et al. (2000) recommend a minimum of six (6) questions. Simultanously, Niederman, Brancheau, and Wetherbe (1991) propose ten (10) or thirty-four (34) questions. Hsu and Sandford (2015) emphasise the Delphi method uses a sequence of questionnaires to collect data for consensus-building from the panel with controlled feedback. Two caveats guided this research in selecting panellists as well as the number of rounds. 1) Experts do not always correctly predict future developments in a field, and 2) multiple rounds can force consensus (Yousuf, 2007). Murphy et al. (1998) support this view that it is unclear whether the number of rounds improves the composite judgment accuracy despite the convergence of the individual opinions. Thus, implying that the study would not be compromised by a possible reduction of the survey rounds from the typical, should the number of participants drop in subsequent rounds. The study was conducted over two rounds of surveys. Although, Jones, Sanderson, and Black (1992) observe the technique is typically administered over three rounds of questionnaires. They note that the number of rounds' determinant is practicality (Jones, Sanderson & Black, 1992). This view is supported by Powell (2003).

The first round used two types of questions viz 5-point Likert-type scales with an open-ended free flow text section for comments about each question in Section One (1). A section for mandatory open comments was included to solicit opinions to generate points for the panellists to consider in the final round. Section Two (2) was limited to five (5)-point Likert-type scale questions with open text at the end. The open text section prompted additional points to be considered that had not been included in the questionnaire (Murphy et al., 1998). Round two (2) repeated the same sections as round one (1), with the mandatory comment's section made optional. A further change on the questionnaire is the issues raised were included on a five (5)-point Likert-type scale in section three (3) of the final round questionnaire. The ranking for the respective sections adhered to the following schema:

Section 1:

Rating: 0 - Do Not Know

1 - Slightly Possible

5 - Significantly Possible

Section 2:

Rating: 0 - Do Not Know

1 - Irrelevant

2 - Minimal Importance

3 - Some Importance

4 - Important

5 - Critical

Section 3:

Rating: 0 - Do Not Know

1 - Irrelevant

2 - Minimal Importance

3 - Some Importance

4 - Important

5 - Critical

This design was chosen to extract significant themes on the context's views, specifically on the research areas (Refer to **Appendix C**). In section one (1): each question required a rating on the linkages' attainability. The linkages were based on the proposed conceptual framework presented in this study. Additionally, the panellist's recommendations on how the respective linkages in the model can or cannot be achieved were sourced. The Likert-type scale of questions was followed by open-ended questions to elicit issues to be considered for 2019 and 2024.

This round was run from November 29, 2019, to December 9, 2019; the survey questions were loaded on Google Forms. Google profiles were created for panellists to generate login details to access the survey on Google Forms. The generated log-on details were confidentially communicated to panellists via their private email accounts. The communication also contained the link to the round’s survey.

The second round, which ran from December 15, 2019, to April 27, 2020, honed in on the significant themes elicited over round one through the open-ended responses. Only in this round was this information used to create a closed five (5)-point Likert-type scale. Murphy et al. (1998) assert the feedback's importance is the only communication among the panellists. For this particular round, the panellists were informed that consensus was measured by consistently calculating the median scores between rounds. Feedback on the questionnaire was presented as the frequency distribution of the individual questions' responses from the previous round. These were presented together with the median, mode, the first and third quartile values, including the interval quartile range. A detailed discussion of the tools of analysis follows in the next sub-section (section 3). Lastly, issues panellists raised in free-flowing comments in the previous round were converted to closed-ended Likert-type questions for round two (2).

These free-flowing comments from the previous round were included in the second round. The comments were coded for themes that occurred on a rating amongst the panellists (Saldaña, 2009). This coding means, for instance, panellists' comments who rated three (3) on an issue and made a comment had their comments coded for themes. From these initial themes, major themes within the comments were then identified. The comments that best articulated the common issues among the panellists within a ranking were quoted. This quote selection procedure was followed for feedback for all the ratings. Furthermore, the comment which included the most diverse topics for consideration were selected. For instance, when a ranking included diverse ideas, all of the comments were quoted.

More characteristics of the Delphi Technique can be found in Powell (2003), Loughlin and Moore (1979) and, Hsu and Sandford (2015). In the next section, data analysis and interpretation are discussed.

3.7 Data Analysis and Interpretation

The collected data were analysed using descriptive and inferential statistics. Using these analyses statistics aligns with the research paradigm, design and procedure of this sequential exploratory mixed methods study as discussed in sub-section 3.3. Statistics. Additionally, this analysis approach is appropriate for Likert scales discussed in sub-section 3.6 and the required coding of comments submitted by the panel.

According to Leedy and Ormrod (2015), Likert scales make use of ordinal measurement scales. Ordinal scales refers to one (1) of the four measurement scales categories. The complementary categories include nominal, interval, and ratio scales (Walliman, 2010; Bhattacherjee, 2012; Creswell, 2014; Leedy & Ormrod, 2015). Figure 3.4 summarises the scale levels.

Units of measurement:

- Nominal: categorise into boxes, names.
- Ordinal: prioritise according to relative values, put into order.
- Interval: sort according to measured value.
- Ratio: measure in relation to a zero value.

Figure 3.4: Summary of Levels of Measurement. Source: Walliman (2010: 77)

Ordinal scales compare pieces of data and produce relative assessments, i.e. rank-ordered data (Bhattacherjee, 2012; Leedy & Ormrod, 2015). In this study, the scale is used in Sections one (1)-to three (3) of the surveys in both rounds. Although not used in this study, the complement of the measurement scales is discussed briefly.

Nominal scales (also known as categorical scales) assign a name to data points. Therefore, they confine the meaning of data points' names, i.e. making them distinguishable from each other (Bhattacherjee, 2012; Leedy & Ormrod, 2015). Interval scales have two characteristics (i) equal units of measurement (ii) an arbitrarily established zero point (Bhattacherjee, 2012; Leedy & Ormrod, 2015). Interval scales allow for more advanced statistical analyses relative to nominal and ordinal scales (Walliman, 2010; Leedy & Ormrod, 2015). Ratio scales, like interval scales, have equal units. However, interval scales differ from interval scales in that interval scales have an absolute zero point (Leedy & Ormrod, 2015). An additional characteristic of ratio scales is their ability to represent values in multiples of fractional parts that capture accurate ratios (Walliman, 2010).

The use of the measurement scales advances to the application of specific statistical analyses tools. These are summarised in Table 3.3. Table 3.3 shows the characteristics of the measurement scales and links them to the specific statical analyses tools. In support of the recommendations made by Leedy and Ormrod (2015), the evidence presented by Hsu and Sandford (2015) advocates for the use of measures of central tendency (mean, median, and mode) and level of dispersion (standard deviation and interquartile range). Measures of central tendency and the level of dispersion are recommended as useful to present the panellists' collective judgment (Hsu & Sandford, 2015).

Table 3.3: The Classification of the Measurement Scales and the related Statistical Analyses. Source: Leedy and Ormrod (2015)

	Measurement Scale	*Characteristics of the Scale*	*Statistical Possibilities of the Scale*
Non-Interval Scales	Nominal scale	A scale that "measures" only in terms of names or designations of discrete units or categories	Enables one to determine the mode, percentage values, or chi-square
	Ordinal scale	A scale that measures in terms of such values as "more" or "less," "larger" or "smaller," but without specifying the size of the intervals	Enables one also to determine the median, percentile rank, and rank correlation
Interval Scales	Interval scale	A scale that measures in terms of equal intervals or degrees of difference, but with an arbitrarily established zero point that does not represent "nothing" of something	Enables one also to determine the mean, standard deviation, and product moment correlation; allows one to conduct most inferential statistical analyses
	Ratio scale	A scale that measures in terms of equal intervals and an absolute zero point	Enables one also to determine the geometric mean and make proportional comparisons; allows one to conduct virtually any inferential statistical analysis

In this study, the median, and the interquartile range (IQR) are used accordingly. When using the median to measure consensus, disagreement is defined as an incident in which one-third of the panellists rate a statement at opposite ends of the scale. This spread in rating means that consensus has not been reached (McMillan, King & Tully, 2016). Sackett et al. (1996) and Schmidt (2001) recommend an IQR greater than 2.25 marks, suggests a difference in opinion.

The recommendations made by McMillan, King, and Tully (2016), Sackett et al. (1996) and Schmidt (2001) are used in this study to determine consensus and spread of opinion. Additionally, the learning effect is measured by the difference in mean between the two rounds. Lastly, the second and subsequent round results were statistically analysed using the chi-squared test and paired t-tests.

3.8 **Validity and Reliability**

In this sub-section, external (3.8.1) and internal (3.8.2) validities are discussed. This sub-section is concluded with a discussion on reliability (3.8.3).

3.8.1 External Validity

Validity relates to the instrument's integrity used to measure what is required (Mohajan, 2017). Participant bias was anticipated to manifest from both the participants and the researcher. The participants' biases were dealt with through the subsequent round of the questionnaire. This round allowed the participants to reflect on their responses against those of their co-panellists. The reflection was anticipated to eliminate or reduce variance in the spread of answers because consensus was reached through the experts' own experiences contrast against the fellow panellists. This triangulation achieves validity and reliability (Sackett et al., 1996; Schmidt et al., 2001).

Linstone and Turoff (2002) support this argument and add that the panellists' heterogeneity assures the validity of the results. Validity guarantees reliability. However, reliability is not a condition for validity. Furthermore, Murphy et al. (1998) note that there is no empirical evidence that the panel size affects the reliability or validity of consensus processes. This technique builds the merit of the research mainly on the panel's qualities, rather than statistical merit (Powell, 2003). The number of successive rounds coupled with the heterogeneity of the panellists assures external validity. External validity (transferability) is concerned with the generalisability of the study's results to other contexts (Bhattacherjee, 2012; Creswell, 2014; Mohajan, 2017).

It is critical that generalising across populations (population validity) is distinguished from generalising to well-defined target populations, organisations, contexts, or time (ecological validity) (Drost, 2011; Bhattacherjee, 2012). This area of study could be generalised to the FMCG industry in South Africa because this is the context within which the participants practice. Furthermore, it is assumed, based on the experts' profiles, in terms of academics and professional ranks, roles, and experience, that this study's results could be applied in FMCG industries in other contexts. Provided the environments are similar to those of South Africa, with all other factors held constant.

3.8.2 Internal Validity

Internal validity (credibility) concerns the researcher's ability to draw correct inferences from the data about the population (Leedy & Ormrod, 2015). It indicates the legitimacy of the results of the study as determined by the manner in which the participants were selected, data were recorded, or analyses were conducted (Mohajan, 2017). Validity is addressed by Murphy et al. (1998), suggesting that it can be achieved through:

i. Comparison against a standard, e.g. using the results of a randomised-controlled trial's results that have not been disclosed to the Delphi panellists.
ii. Using criterion-related (predictive and concurrent) validity by comparing the inquiry results with results from other sources.
iii. Evaluating the logic of the group, e.g. testing the spread of the responses for a common situation.
iv. Evaluating the face validity, Havins (2006) suggests the following questions: "Do intended users understand the design? Does it make sense to them? Do they appreciate the implications of comparing

program A with Program B? Do they know what the design includes, or does it not include, in a control group? Is the sample size sufficiently large to be believable?"

Other users of the method have used multiple researchers to interpret the responses to get better triangulation. Although not popular, Crotty (1992) conducted interviews on responses regarding high agreement and low agreement issues.

Owing to the nature of the study and the novelty of the approach under study, Murphy et al. (1998) prescribe (iii) and (iv) as most suited for this research. Drost (2011) refers to (iii) on the above list as convergent and discriminant validity.

The instrument was designed and constructed on a firm theoretical basis from other instruments with proven reliability and validity. The questionnaire was designed to eliminate the learning effect. This effect was eliminated by constructing user-friendly and visually appealing questionnaires. This construction approach ensured taking the study would not be time-consuming. Additionally, a participant would only be required to respond to the questions once.

The participants were fully aware of the study's objectives because these were communicated during the recruitment process and reiterated during round one (1) of the questionnaire. Panellist participation was voluntary; responses were handled to maintain anonymity, and feedback was given anonymously. Thus, the study is deemed internally valid because the researcher is not aware of uncontrolled threats to the validity that arose in the course of the study.

3.8.3 Reliability

Reliability relates to the extent the instrument will yield consistent results given the same conditions; on all occasions, reflective of the total population under study, i.e. it is about the results' stability. This characteristic concerns the degree to which the measuring tool moderates random error (Drost, 2011; Mohajan, 2017). Reliability was addressed by successive rounds of the constructed Delphi questionnaire. The second round allowed the panellists to evaluate and reflect on their responses as well as weigh them against those of the co-panellists (Sackett et al., 1996; Schmidt et al., 2001).

3.9 Ethics

The questionnaire was administered electronically. All other communication with the panellists was conducted via email, except for the Linkedin InMail used in recruitment communication. Information about the participants was kept anonymous. Their responses were saved on a private password-protected data storage cloud account. Results were shared with the panellists as feedback according to the dictates of the technique, solely for the study's progress. Additional results will be shared in the final report. Participants were given an option to indicate interest to be included in the circulation of the final report for the study's findings.

The data collected from the study will be disposed of after six (6) months from the study's completion date. The ethical requirements for this study were conducted in line with the University of the Witwatersrand’s School of Mechanical, Industrial and Aeronautical Engineering stipulations.

CHAPTER 4: DATA ANALYSIS AND RESULTS

4.1 Introduction

This chapter presents the results obtained through the two-round Delphi Technique online questionnaires described in Chapter 3. The chapter begins with the panellists' demographical profile (4.2), which includes the statistical significance test results of the successive Delphi Technique rounds. This analysis is followed by the results and analysis of each hypothesis (4.3) on the proposed conceptual framework. After that, the summary of the results is presented (4.4), concluding this section.

4.2 Demographic Profile of the Panellists Composition

4.2.1 Panel Characteristics

The study targeted a minimum of fifteen (15) panellists. To achieve this, forty-four (44) potential panellists were approached, with sixteen (16) panellists participating in round one of the Delphi Study. Round two, the final round, had thirteen (13) panellists from the original lists of panellists. The three (3) panellists who did not continue from the initial round to complete the final round questionnaire; communicated that their circumstances did not allow further participation.

The following demographic data is based on the sample that participated in both rounds of the study. The statistical analyses for the entire study were conducted on data collected from both rounds. The chosen statistical analyses approach is in line with the approach of handling databases from exploratory sequential mixed methods research (Melnyk et al., 2009; Creswell, 2014). Melnyk et al. (2009) built their database by combining the two Delphi study rounds' results. According to Creswell (2014), for exploratory sequential mixed methods research designs, the database generated from the qualitative round of the research, round one, can be added to the subsequent quantitative round of the research for analyses.

Figure 4.1 shows the academic qualifications of the panellists who participated in round one of the study.

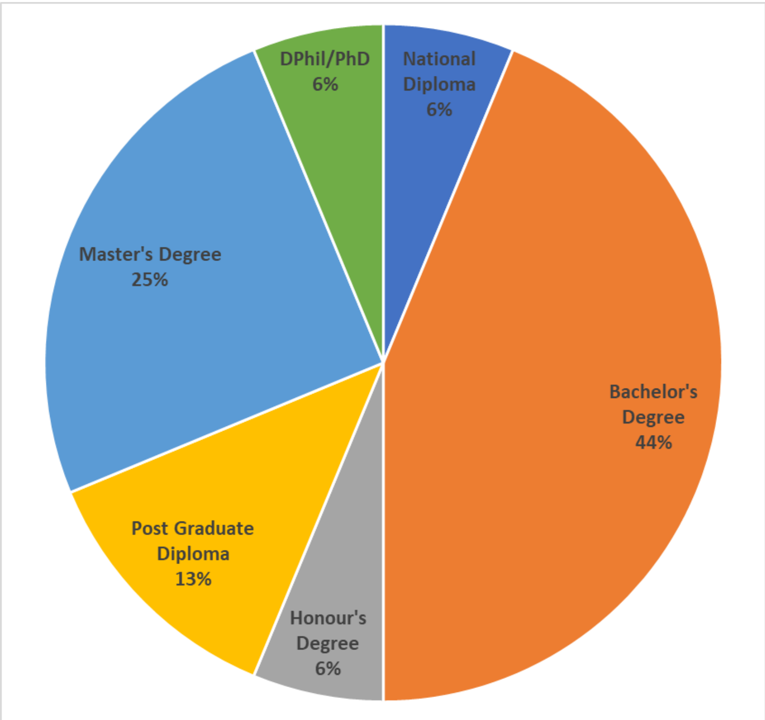

Figure 4.1: The highest level of education completed profile of the round one Panellists (n=16)

Of the total sample of sixteen (16) panellists who participated in the first round of the study. 6% hold a National Diploma; 44% hold a Bachelor's degree; 6% hold an Honour's degree; followed by 13% that hold a Postgraduate Diploma; 25% hold a Master's degree; while 6% hold a qualification at DPhil/PhD (i.e. doctoral/doctorate) level.

Figure 4.2 shows the academic qualifications of the panellists who participated in round two of the study.

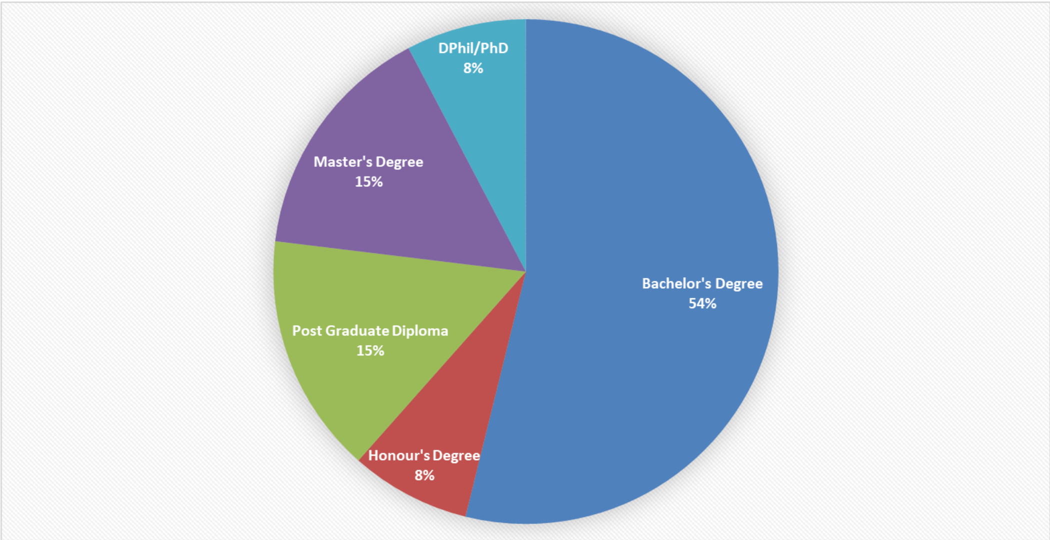

Figure 4.2: The highest level of education completed profile of the round two Panellists (n=13)

From the total sample of thirteen (13) panellists who participated in round two of the survey, 54% hold a Bachelor's degree; 8% hold an Honour's degree; followed by 15% that hold a Postgraduate diploma; 15 % hold a Master's degree; while 8% hold a qualification at DPhil/PhD (i.e. doctoral/doctorate) level.

Figure 4.3 is a graphical representation of the industry breakdown. The sixteen (16) panellists who participated in round one were from three primary industries: 81% were from Fast Moving Consumer Good areas (including confectionery, cosmetics, food and beverage, and original equipment manufacturer), 6% Pharmaceutical and 13% Information and Communication Technology.

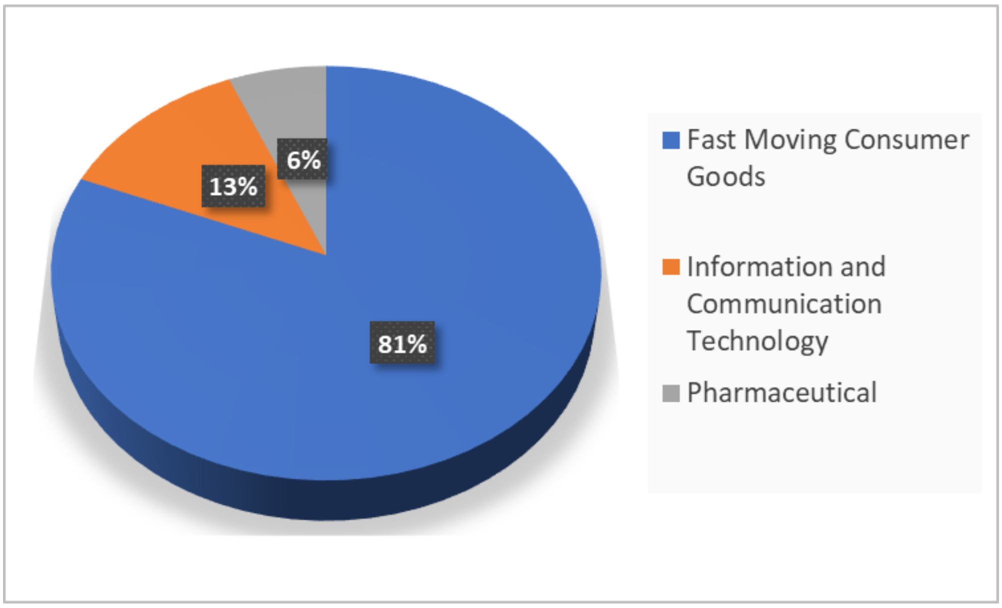

Figure 4.3: Industry Description of the Panellists (n=16) in round one

Figure 4.4 is a graphical representation of the industry breakdown of the round two participants. The thirteen (13) panellists who participated in the final round were from two primary industries: 92% were from Fast Moving Consumer Good areas (including confectionery, cosmetics, food and beverage and original equipment manufacturer) and 8% Information and Communication Technology.

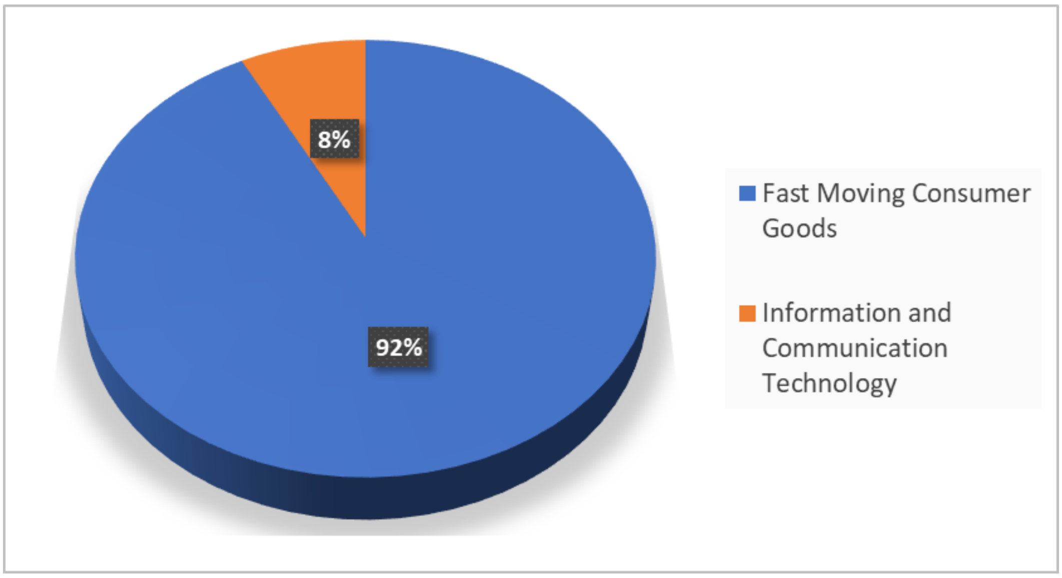

Figure 4.4: Industry Description of the Panellists (n=13) in round two

Figure 4.5 is a graphical representation of the management level of the panellists in round one of the study:

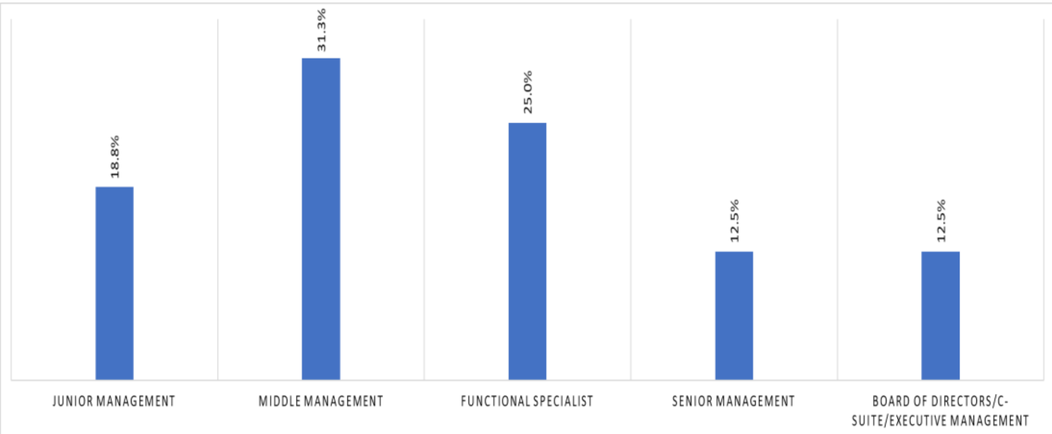

Figure 4.5: Position in organisation of the Panellists shown as a percentage of the panel size for round one (n=16)

As shown in Figure 4.5, 50.0% of the panellists, i.e., 31.3% and 18.8%, comprise individuals who occupy roles in Junior and Middle Management, respectively. The roles occupied by the complementary 50.0% of the total number of panellists comprised of Functional Specialists who accounted for

25.0% of the panellists followed by Senior Management and Board of Directors/C-Suite/Executive Management each at 12.5%.

Figure 4.6 is a graphical representation of the management level of the panellists in round two of the study:

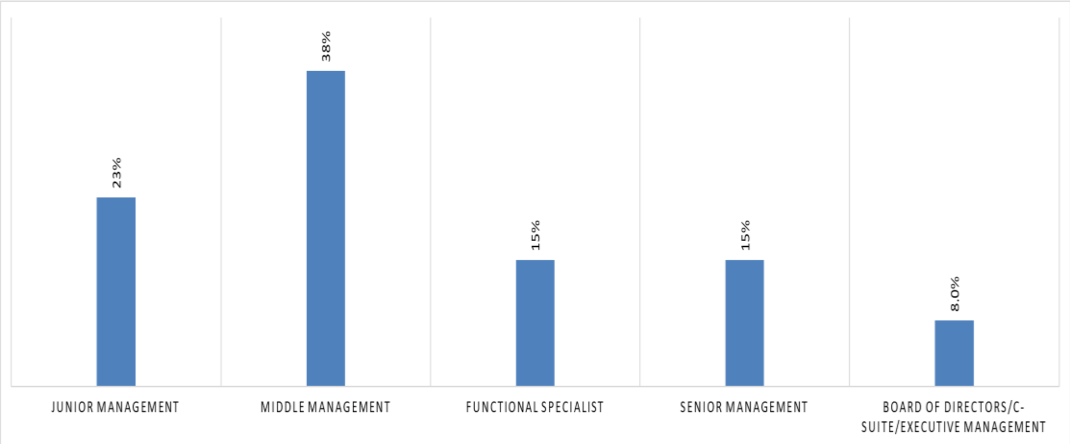

Figure 4.6: Position in organisation of the Panellists shown as a percentage of the panel size for round two (n=13)

Figure 4.6 shows a slight excess of 60.0% of the panellists, i.e., 38.5% and 23.1%, comprised of individuals who occupy roles in Junior and Middle Management, respectively. The roles occupied by the complementary 40.0% of the total number of panellists comprised of Functional Specialists and Senior Management, each accounting for 15.4% of the panellists, lastly, followed by Board of Directors/C-Suite/Executive Management at 8.0%.

Figure 4.7 graphically represents the experience, in the number of years, of the round one panellists.

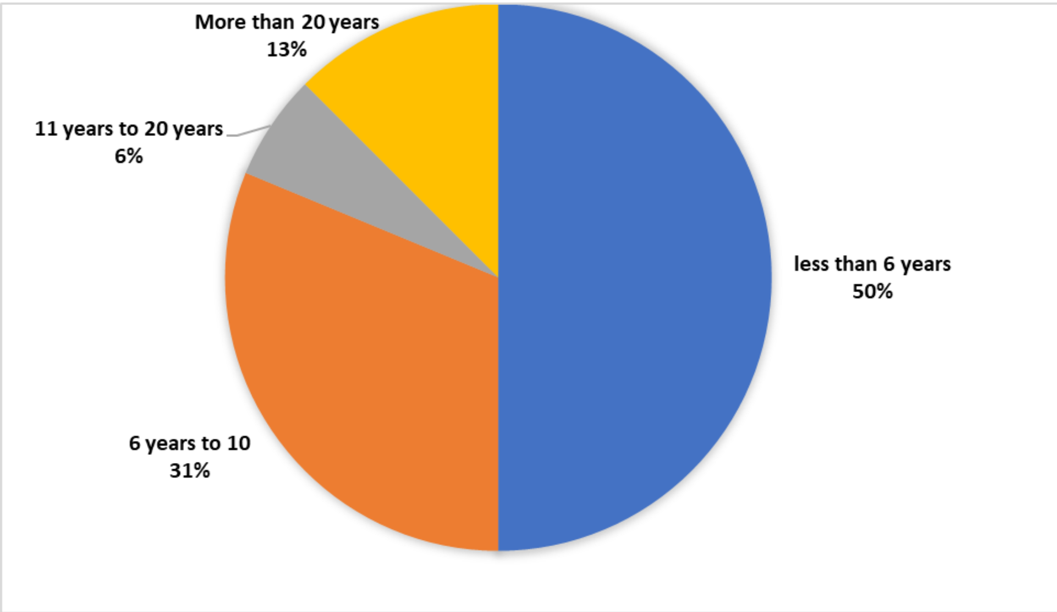

Figure 4.7: Experience, in number of years, of Panellists shown as a percentage of the panel size (n=16) for round one

50% of the panellists have under six (6) years of experience; this majority is followed by 31% of the panellists with years of experience between 6-10 years. With more than 20 years of experience, panellists made up 13% of the panel; the remaining 6% comprises the panellists with 11-20 years of experience.

Figure 4.8 graphically represents the experience, in number of years, of the panellists in round two.

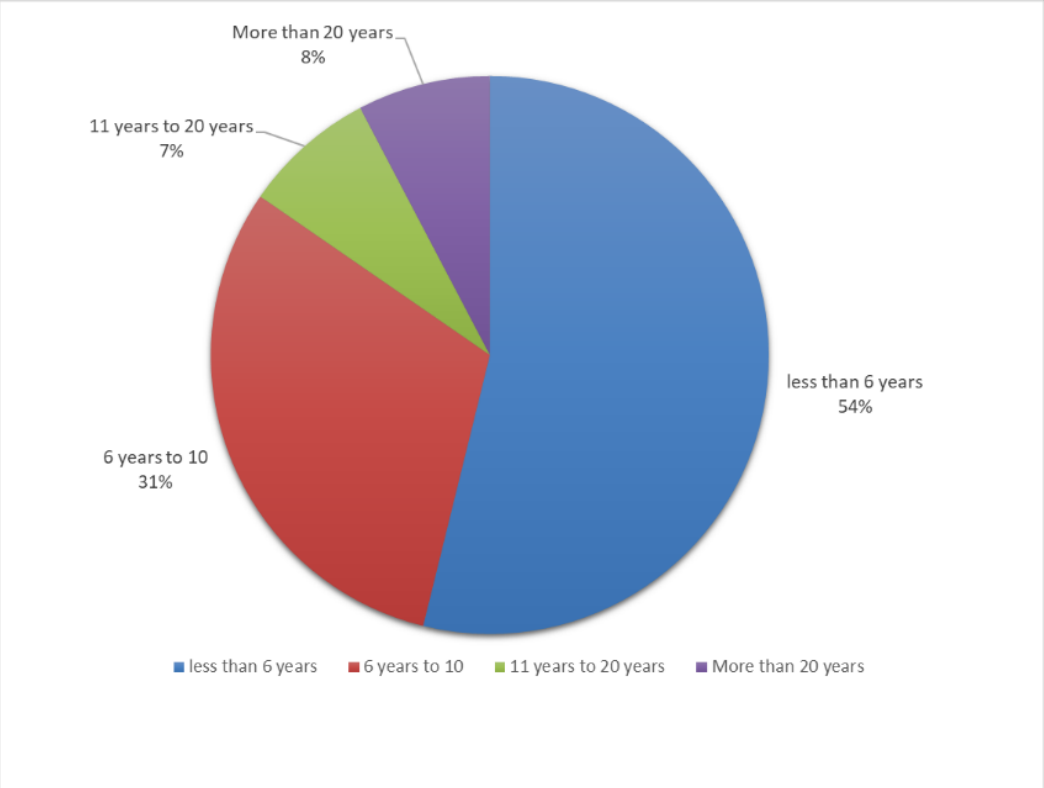

Figure 4.8: Experience, in number of years, of Panellists shown as a percentage of the panel size (n=13) for round two

Round two of the study comprised 47% of the panellists with under six (6) years experience; this majority is followed by 31% of the panellists with years of experience between 6-10 years. Panellists with more than 20 years' experience made up 8% of the panel; the remaining 7% was made up of the panellists with 11-20 years of experience.

4.2.2 Statistical Difference Significance

Melnyk et al. (2009) use the sum of the responses from the successive rounds of a Delphi study as the total number of responses to compute the χ^2 test probabilities. This is in line with Creswell's (2014) recommendation on how to build and analyse databases in sequential exploratory mixed methods research designs, as mentioned in section 4.2.1. This study follows the same approach and uses it to validate the panel composition through the paired samples t-test. Although Melnyk et al. (2009) did not use the χ^2 test to test hypotheses to assess the relationships between constructs; it is done in this research. To conduct the χ^2 test, the databases from the successive rounds of the Delphi study are combined.

Since the Delphi study questionnaires allowed a “0-Do Not Know” rating option, a “0-Do Not Know” response is truncated from the calculation of the total responses for the succeeding computations in the analysis (Underhill & Bradfield, 2013). Underhill and Bradfield (2013) demonstrate this is practice when handling statistical categories in χ^2 test probabilities that do not meet the minimum requirement of 5 responses for each response option. Where applicable, panellists who selected the “0-Do Not Know” rating option as their response; for statistical analysis, their selection was added to the number of ratings in the “1” rating selection. Adding a rating to a category is in line with the recommendation by Underhill and Bradfield (2013).

In count and percentage, the rating frequencies for the constructs identified from the literature to develop the conceptual framework in the first section of the questionnaire are shown in Table 4.1. These frequencies are shown with the total number, *n*, used to test for the respective hypotheses in Table 4.1:

Table 4.1: Table of Rating Frequencies and *n* used in hypothesis testing for the questions

Issue	Unit of Measure	Rating Frequencies 1	2	3	4	5	0	n used in hypothesis
1. Do you think consumer preferences can be extracted from big data?	Count	0	0	0	16	13	0	29
	Percentage	0%	0%	0%	55%	45%	0%	
2. Do you think consumer preference data can improve product development?	Count	0	0	1	6	22	0	29
	Percentage	0%	0%	3%	21%	76%	0%	
3. In your view, do you believe that product development can lead to improvements in process parameters in manufacturing?	Count	0	1	9	6	13	0	29
	Percentage	0%	3%	31%	21%	45%	0%	
4. Do you think process parameters can impact mass customisation in terms of the manufacturing equipment design and optimisation?	Count	1	2	1	13	11	1	28
	Percentage	4%	7%	4%	46%	39%	4%	
5. Do you think consumer preferences affect mass customisation in terms of the manufacturing equipment design and optimisation?	Count	2	0	5	12	10	0	29
	Percentage	7%	0%	17%	41%	34%	0%	
6. Do you think it is possible to optimise product development and mass customisation (in terms of the manufacturing equipment design and optimisation?)	Count	1	0	3	14	10	0	28
	Percentage	4%	0%	11%	50%	36%	0%	
7. Do you believe mass customisation (equipment design, including its optimisation) can be linked to flexible manufacturing systems?	Count	1	3	1	12	11	1	28
	Percentage	4%	11%	4%	43%	39%	4%	
8. Do you believe flexible manufacturing systems can improve plant utilisation?	Count	1	0	2	11	14	1	28
	Percentage	4%	0%	7%	39%	50%	4%	
9. Do you think big data can improve plant utilisation?	Count	2	0	1	11	15	0	29
	Percentage	7%	0%	3%	38%	52%	0%	

The total number of responses, even with the omission and merging of "0-Do Not Know" ratings in questions 4, 6 and 8, met the requirements, i.e. minimum of 5 responses, for the application of the χ^2 test (Underhill & Bradfield, 2013).

Furthermore, panel composition for the two rounds was assessed to weigh the impact of the drop-out rate. This assessment was done using χ^2test at $\alpha = 0.05$. The results were $\chi^2 = 0.3103, and\ p = 0.577,$ which indicate no significant difference in the panel composition between the successive rounds. Table 4.2 shows the number of participants in the successive rounds:

Table 4.2: Number of Panellists in each round.

Round	Number of Panellists
1	16
2	13
Total	**29**

4.3 Theoretical Model and Hypotheses Test

Before proceeding with the presentation of the results from the statistical analyses conducted on the data generated from the two-round Delphi study, it is important to point out that the sample data set is small. Despite this, the study's sample size meets the requisite minimum number of panellists for Delphi research studies (Fink et al., 1984; Hasson, 2000; Thangaratinam & Redman, 2005; Sahari et al., 2018). Various scholars appear to suggest varied acceptable minimum numbers for panellists required to participate in a credible Delphi study. Reid (1988) suggests ten (10) as the minimum number of panellists. In comparison, Thangaratinam and Redman (2005) suggest a minimum of four (4) panellists. Seven (7) or eight (8) panellists are suggested by Sahari et al. (2018).

Although this study's sample meets the minimum size requirement for a Delphi study, the sample size constrains the range of statistical tools that can be used for analysis. Thus, the χ^2 test, which is a non-parametric test, is used and carried out at significance level $\alpha = 0.05$ for analyses of the results of this study. The minimum requirement is five (5) responses for each response option for the successful use of the χ^2 test (Underhill & Bradfield, 2013). The significance level is the expression of the probability that the null hypothesis will be rejected when, in actuality, it is true (Underhill & Bradfield, 2013). χ^2 test is suitable for application on small samples with a major drawback in that it does not test for interaction effects (Melnyk et al., 2009; Bhattacherjee, 2012). Therefore, in this study, interaction effects (i.e., how one question affects another question) are not considered and may be an investigation area in future studies. In order to address the objectives of this study the χ^2 test has been applied to assess the linkages between the constructs in the form of hypotheses testing.

Table 4.3 shows the χ^2 test, p-values, and hypotheses. P-value is defined as the probability of finding a test-statistic value equal to or larger than the observed test statistic in an instance of random samples of the same size from the same population used in the same sample (Underhill & Bradfield, 2013).

Table 4.3: χ^2 −test hypotheses test results at significance, $\alpha = 0.05$

Question	Hypotheses	p-values
9	**H1 and H2**: Big data is positively related to plant utilisation.	$p < .001$
1	**H3**: Big data is positively related to consumer preferences.	$p < .001$
2	**H4**: Consumer preference data are positively related to product development.	$p < .001$
3	**H5**: Product development is positively related to process parameters in manufacturing.	$p < .001$
4	**H6**: Process parameters are positively related to mass customisation in terms of the manufacturing equipment design and optimisation.	$p < .001$
6	**H7 and H8**: Product development is related to mass customisation (in terms of the manufacturing equipment design and optimisation).	$p < .001$
7	**H9**: Mass customisation (equipment design, including its optimisation) are positively related to flexible manufacturing systems.	$p < .001$
8	**H10**: Flexible manufacturing systems are positively related to plant utilisation	$p < .001$
5	**H11 and H12**: Consumer preferences are related to mass customisation in terms of the manufacturing equipment design and optimisation.	$p < .05$

The p-values for all the hypotheses are below the significance value of $\alpha = 0.05$ from the χ^2test. This result means that these dependent hypotheses can be accepted at significance level $\alpha = 0.01$, with the exception of H11 & H12. These hypotheses are acceptable at a higher significance level of $\alpha = 0.05$. The higher acceptance criterion satisfies statistical dictates. Therefore, it can be concluded that there are linkages between the constructs mentioned in the respective hypotheses, as shown in Table 4.3. At this level of significance, $\alpha = 0.05$, this study's proposed conceptual framework is validated.

4.3.1 Reliability and Validity of Measurement Scales

Reliability and validity are measured by the reduction in the spread of the responses; this is achieved as consensus is reached in the respective rounds; this is measured in IQR. This convergence in opinion is an effect of the panellists judging their responses against those of their co-panellists (Sackett et al., 1996; Schmidt et al., 2001).

Delphi studies typically make use of a combination of measures of central tendency to present the collective responses (Hasson, 2000; Schmidt et al., 2001; Akkermans et al., 2003; Ogden et al., 2005; Thangaratinam & Redman, 2005; Yousuf, 2007; Melnyk et al., 2009; Giannarou & Zervas, 2014; Hsu & Sandford, 2015). Measures for central tendency include means, medians, or modes, paired with the level of dispersion measures, i.e. standard deviation and (or) interquartile ranges (IQR) (Hasson, 2000; Schmidt et al., 2001; Akkermans et al., 2003; Ogden et al., 2005; Thangaratinam & Redman, 2005; Yousuf, 2007; Melnyk et al., 2009; Giannarou & Zervas, 2014; Hsu & Sandford, 2015).

For this study, the combination of the median with the mean are used for central tendency measurement. Since the data is ordinal, the median is considered the most appropriate measurement scale (Bhattacherjee, 2012; Giannarou & Zervas, 2014; Hsu & Sandford, 2015) used in this study. Additionally, for each issue, the mean rating is reported and used to measure the difference in mean ratings on the same issue between rounds one (1) and two (2) in Table 4.4 and the periods of interest, 2019 and 2024, for tables 4.4 and 4.5. For the former, Table 4.4, the difference in mean is used to interpret the learning effect. This measurement means the shift of the response on which the panellists converge is measured. Therefore, it can be expected that this measure would indicate the panellists were, in general, learning from each other.

For the latter Tables 4.4 and 4.5, the difference in means is used to measure the direction of growth (or decline) in the importance of the considered issues. The outcome from this measurement is, in turn, used as a proxy to paint a picture about the anticipated complexity that the market preference data technology adds to the PLM and supply chain work-processes over time (Melnyk et al., 2009). Lastly, an IQR of less than two point five (2.5) has been used to define consensus (Kittell-Limerick, 2005; Giannarou & Zervas, 2014).

Table 4.4 shows the median, IQR, mean and the difference between the mean in rounds (one) 1 and two (2).

Table 4.4: Consensus levels on the linkages from big data to plant utilisation

Issue	Round 1			Round 2			Δ
	Median	IQR	Mean	Median	IQR	Mean	Mean
1. Do you think consumer preferences can be extracted from big data?	4.5	1	4.50	4	1	4.38	-0.12
2. Do you think consumer preference data can improve product development?	5.0	1	4.63	5	0	4.85	0.22
3. In your view, do you believe that product development can lead to improvements in process parameters in manufacturing?	4.0	2	3.88	5	1	4.31	0.43
4. Do you think process parameters can impact mass customisation in terms of the manufacturing equipment design and optimisation?	4.0	2.25	3.56	4	1	4.46	0.90
5. Do you think consumer preferences affect mass customisation in terms of the manufacturing equipment design and optimisation?	4.0	2	3.94	4	1	4.00	0.06
6. Do you think it is possible to optimise product development and mass customisation (in terms of the manufacturing equipment design and optimisation?)	4.0	1	4.06	4	1	4.25	0.19
7. Do you believe mass customisation (equipment design, including its optimisation) can be linked to flexible manufacturing systems?	4.0	1.5	3.69	4	1	4.15	0.47
8. Do you believe flexible manufacturing systems can improve plant utilisation?	4.0	1	4.06	5	1	4.31	0.25
9. Do you think big data can improve plant utilisation?	4.0	1	4.19	5	1	4.38	0.20

The difference in mean is significant for question 4 at 0.9, which shows there was a positive shift in the opinion of the panellists from round one (1) to round two (2). The relationship being investigated is between process parameters and mass customisation in terms of the manufacturing equipment design and optimisation. Incidentally, this shift reflects in both the median, from 3.56 to 4.46, as well as in the IQR, from 2.25 to 1. The least shift by an interval in the mean is seen in question 5, from 3.94 to 4, which links consumer preferences and mass customisation in terms of the manufacturing equipment design and optimisation. There is no visible shift in the other statistical measures that are reported. Notably, question 1, which links consumer preferences and big data, had a negative shift in means, from 4.5 to 4.38. This shift is also seen in the medians for rounds 1 and 2 from 4.5 to 4. An average rating of 4 or higher was considered as very possible. The results above show that the linkages are highly probable.

Round 1 showed slightly higher IQR values for questions 3, 4, 5, and 7, which imply a slight divergence of views. In round 2, the IQR values dropped to 1, showing convergence in the panellists' opinion. Therefore, it can be concluded that the internal validity and reliability for the constructs and associations in the proposed framework have been achieved (Murphy et al., 1998).

4.3.2 Ecological Validity

This sub-section is primarily concerned with the final research objective of this study. Firstly, the impact of consumer preferences on the equipment design; and how these preferences subsequently affect the design constraints is addressed. Secondly, it deals with the ecological validity, particularly as it relates to time and technological contexts (Drost, 2011; Bhattacherjee, 2012). The context is considered as it relates to big data and the associated analytics capabilities. Additionally, how big data outputs, including consumer preferences and equipment management data, impact the structural design and the performance measurement of the value chain. Lastly, the role this big data output plays in the leadership and management of the different contributors to the value chain within the FMCG industry. Furthermore, the evolution big data outputs impose on these contributors is considered against time, i.e., current versus five (5) years into the future.

To achieve these enumerated outcomes, the panellists assessed the issues identified from literature at two distinct time points: *importance now*, the year 2019, and *importance 5 years from now,* the year 2024 (Melnyk et al., 2009). Table 4.5 shows the median, IQR, mean, the difference between the successive rounds for 2019 (∆Mean Now) and 2024 (∆Mean 5 years from now), respectively. The p-values from the paired samples t-test were applied to round two (2) results. Round two (2) results were used to assess whether or not the difference in the ratings assigned to today's issues and to five years from now were significant at significance level $\alpha = 0.05$. Round two results were used as they represent the converged responses of the panellists in terms of consensus (measured in mean and median) and in the spread of opinion (IQR).

Table 4.5: The level of consensus and the p-values obtained from the paired t-test at $\alpha = 0.05$.

Issue	Round 1			Round 2			Δ Mean NOW	Δ Mean 5 years from now	p-value
	Median	IQR	Mean	Median	IQR	Mean			
1.Leadership in data analytics-NOW	4.00	2.00	3.56	4.00	1.00	3.92	0.36		0.022
1A Leadership in data analytics-5 years from now	5.00	1.00	4.31	5.00	1.00	4.62		0.30	
2. Collaboration within design, manufacturing and operations-NOW	4.50	1.00	4.44	5.00	1.00	4.69	0.25		0.006
2A. Collaboration within design, manufacturing and operations-5 years from now	4.00	1.00	4.25	4.00	1.00	4.15		-0.10	
3. Identifying and utilising consumer preferences to improve product development-NOW	4.00	2.00	4.00	4.00	1.00	4.46	0.46		**0.500**
3A. Identifying and utilising consumer preferences to improve product development-5 years from now	4.50	1.00	4.38	4.00	1.00	4.46		0.09	
4. Performance metrics across the value chain from consumer preferences to product development to operations and plant utilisation-NOW	4.00	0.50	3.81	5.00	1.00	4.54	0.73		**0.083**
4A. Performance metrics across the value chain from consumer preferences to product development to operations and plant utilisation-5 years from now	4.00	1.00	4.25	5.00	1.00	4.69		0.44	
5. Changing/re-aligning performance measurement across the value chain from consumer preferences to product development to operations and plant utilisation-NOW	4.00	0.25	3.94	5.00	1.00	4.46	0.52		**0.500**
5A. Changing/re-aligning performance measurement across the value chain from consumer preferences to product development to operations and plant utilisation-5 years from now	4.00	1.25	4.06	4.00	1.00	4.46		0.40	
6. Managing product development by drawing on the capabilities of big data-NOW	4.00	2.00	3.88	5.00	1.00	4.54	0.66		0.009
6A. Managing product development by drawing on the capabilities of big data- 5 years from now	4.00	1.00	4.19	4.00	0.00	4.15		-0.03	
7. Managing visibility and control of the value chain through the use of big data-NOW	4.00	1.25	4.06	5.00	1.00	4.54	0.48		**0.137**
7A. Managing visibility and control of the value chain through the use of big data-5 years from now	4.00	1.00	4.19	5.00	0.00	4.77		0.58	
8. Developing and maintaining appropriate Communication and collaboration across the value chain-NOW	4.50	1.00	4.44	5.00	1.00	4.62	0.18		**0.292**
8A. Developing and maintaining appropriate Communication and collaboration across the value chain-5 years from now	4.50	1.00	4.44	5.00	1.00	4.69		0.25	

The change in the mean between rounds one (1) and two (2) for 2019, *ΔMean NOW*, shows that the most significant change in opinion by mean is on issue 4, from 3.81 to 4.54. The issue addresses the level of importance of ‘performance metrics across the value chain from consumer preferences to product development, to operations, and plant utilisation at present.’ The shift in opinion between the successive rounds is also visible in the median, while the IQR value for the same question shifted by 0.50.

The lowest shift is in *ΔMean NOW* is by 0.18 for issue 8, which considers the importance of ‘developing and maintaining appropriate communication and collaboration across the value chain.’ Although the median shifted by 1.00 unit, the IQR value remained constant between the two rounds.

The change in the mean between rounds one (1) and two (2) for 2024, *ΔMean 5 years from now*, shows that the most significant change in opinion by mean was on issue 7A, from 4.19 to 4.77. This question addresses the level of importance of ‘managing visibility and control of the value chain through the use of big data 5 years from now.’ The shift in ratings between the successive rounds is also visible in the median, from 4.00 to 5.00, while the IQR value for the same question shifted from 1.00 to 0.00.

The lowest shift is in *ΔMean 5 years from now* is by 0.09 for issue 3A, which considers the importance of ‘identifying and utilising consumer preferences to improve product development-5 years from now’. Although the IQR remained constant at 1, the median value dropped between the two rounds from 4.50 to 4.00.

Also noteworthy are the two negative shifts in means between the successive rounds, reflected in *ΔMean 5 years from now* of -0.10 and -0.03

for issues 2A and 6A, respectively. The IQR for question 2A, which considers the importance of 'collaboration within design, manufacturing and operations-5 years from now,' remained constant. Contrastingly, the IQR for issue 6A, which considers the importance of 'managing product development by drawing on the capabilities of big data-5 years from now,' dropped from 1.00 to 0.00. The median for this question remained constant at 4.00 for both rounds.

A median of 4.00 or higher was considered critical in line with Melnyk et al.'s (2009), in a Delphi study in reviewing this data. All issues with a median rating of 4.00 were considered critical apart from issue 1. This issue considered the importance of 'leadership in data analytics-NOW.' Its median rating was 3.92, despite a decrease in IQR from 2.00 in round 1 to 1.00 for round 2.

From the eight (8) issues identified in the literature that the panellists assigned ratings, five differences between rounds one (1) and two (2) have p-values over the significance level $\alpha = 0.05$. These questions are the paired 3 and 3A, 4 and 4A, 5 and 5A, 7 and 7A, and 8 and 8A. The increases seen in *ΔMean 5 years from now* for the respective questions and the results from the paired samples t-test suggest there can be an increase in importance of the issues. Also, these results confirm the context of the proposed conceptual framework within the broader technological advances; thus, context validity is achieved. Furthermore, the results support the propositions made on the impact of big data as it relates to consumer preferences and equipment management data on the value chain as it pertains to product and equipment design for maximised plant utilisation.

In addition to the issues identified from the literature, the panellists identified 15 significant issues in round one, the qualitative round, of the Delphi study.

These issues were included in the final round, the quantitative round, so that the panellists could assign them ratings. The rating process followed the same instruction as the assessment of the issues identified in the literature. Table 4.6 shows the median, IQR, mean, and ∆Mean, which is the difference between the mean ratings on the issues for 2019 (∆Mean Now) and 2024 (∆Mean 5 years from now), respectively.

All the issues identified by the panellists had a median rating of 4.00 and 5.00. Thus, they were all considered critical. The IQR ranged from 0.00 to 2.00, which lies below the 2.50 limit used in this study to measure consensus. Some issues received a median rating of 5.00 and an IQR value of 0.00. These issues were considered critical and with no spread in opinion. The highly-rated issues include ‘Consumer privacy. 5 years from Now’, ‘Ethics. Now’, ‘Ethics. 5 years from Now’ and ‘The use of automation and intelligence. 5 years from NOW.’ The highest shift in mean ratings, ∆Mean, between 2019 and 2024 ratings is seen on ‘The use of automation and artificial intelligence. 5 years from NOW.’ The ∆Mean for ‘Change in talent requirements and capability’ was zero showing the mean ratings for the two time periods were constant. The issues with ∆Mean at zero can indicate the panellists view the issue as having no progressive requirement over time. Negative ∆Mean is seen for issues 2, 7, and 8.

The paired samples t-test was carried out on the ratings for the 2019 and the 2024 periods. These show that 73.33% of the issues show significant differences at significance level $\alpha = 0.05$. The large number of issues with high statistical significance suggests growth in complexity over time. Therefore, these results strongly suggest the ecological validity of the study. The IQRs were below the 2.25 value, which marks the difference in opinion. Thus, indicating consensus amongst the panellists on the issues they raised. In addition, this level of consensus also marks reliability (Sackett et al., 1996; Schmidt et al., 2001).

Table 4.6: Issues to be considered between now and five (5) years from now as identified by the panellists

Issue	Median	IQR	Mean	Δ Mean	p-value
1. Launching new products in different segments, Like First taste preferable to kids can be decided based on the data available.	4.00	1.00	3.77	0.15	0.083
1A. Launching new products in different segments, Like First taste preferable to kids can be decided based on the data available. 5 years from NOW	4.00	1.00	3.92		
2. Demand planning of developed products	5.00	1.00	4.69	-0.15	0.083
2A. Demand planning of developed products. 5 years from NOW	5.00	1.00	4.54		
3. Understanding the cycle of production throughout the value chain better	5.00	1.00	4.54	0.08	0.292
3A. Understanding the cycle of production throughout the value chain better. 5 years from NOW	5.00	1.00	4.62		
4. Strategic decision making capability improvements	4.00	1.00	4.46	0.23	0.041
4A. Strategic decision making capability improvements. 5 years from NOW	5.00	1.00	4.69		
5. Change in talent requirements and capability	5.00	1.00	4.62	0.00	0.500
5A. Change in talent requirements and capability. 5 years from NOW	5.00	1.00	4.62		
6. Seven day data, process and information cycle appraisal/reporting optimisation	4.00	2.00	3.77	0.15	0.251
6A. Seven day data, process and information cycle appraisal/reporting optimisation. 5 years from NOW	4.00	1.00	3.92		
7. Running field team surveys on daily issues faced by front line staff/teams, thus gathering insights on what and how to improve on an on-going basis	4.00	2.00	4.08	-0.23	0.214
7A. Running field team surveys on daily issues faced by front line staff/teams, thus gathering insights on what and how to improve on an on-going basis. 5 years from NOW	4.00	2.00	3.85		
8. Degree to which big data can improve operational efficiency and can improve customer service.	5.00	1.00	4.38	-0.15	0.274
8A. Degree to which big data can improve operational efficiency and can improve customer service. 5 years from NOW	4.00	1.00	4.23		
9. How quickly the big data can be utilized to deliver results. NOW	4.00	1.00	4.15	0.46	0.041
9A. How quickly the big data can be utilized to deliver results. 5 years from NOW	5.00	1.00	4.62		
10. Understanding the [organisation's] vision in five years. NOW	5.00	1.00	4.38	0.23	0.095
10A. Understanding the [organisation's] vision in five years.5 years from NOW	5.00	1.00	4.62		
11. The important factors which need to be considered when big data is used for monitoring. NOW	4.00	1.00	4.38	0.15	0.218
11A. The important factors which need to be considered when big data is used for monitoring. 5 years from NOW	5.00	1.00	4.54		
12. Consumer privacy. NOW	5.00	1.00	4.38	0.38	0.027
12A. Consumer privacy. 5 years from NOW	5.00	0.00	4.77		
13. Ethics. NOW	5.00	0.00	4.54	0.23	0.169
13A. Ethics. 5 years from NOW	5.00	0.00	4.77		
14. Predictive additional capability. NOW	4.00	2.00	3.62	0.31	0.132
14A. Predictive additional capability. 5 years from NOW	5.00	1.00	3.92		
15. The use of automation and artificial intelligence. NOW	4.00	1.00	4.15	0.62	0.013
15A. The use of automation and artificial intelligence. 5 years from NOW	5.00	0.00	4.77		

4.4 Summary of Results

In summary, the sample size was 16 for the first round and 13 for the final round. The panellists for both rounds consisted of experts who held tertiary education qualifications. The sample of panellists held a minimum of one year of work experience. Using the Delphi Technique, with qualifying experts, ensures the results' validity (Sackett et al., 1996; Schmidt et al., 2001; Turoff & Linstone, 2002). Validity is attained through the feedback from round one that is shared with the panellists to reflect and comment for round two questionnaires (Sackett et al., 1996; Schmidt et al., 2001).

Consensus, measured through the IQR and median, was used to measure the proposed constructs' validity and the respective linkages in the proposed conceptual framework. The results suggest that the identified constructs and linkages are valid. Additionally, the learning effect among the panellists was measured by the difference in means between the successive rounds and their rated issues. The difference in means showed a shift in all of the issues, except for an issue raised by the panellists. The issue is ‘Change in talent requirements and capability.’ This issue was rated at a median of 5.00 with an IQR of 1.00 for both rounds. This result suggests this issue is equally critical for the periods under consideration. Moreover, a non-parametric statistical analysis tool, the χ^2 test was used to test the hypotheses of the proposed associations of the constructs in the conceptual framework. The results for the overall study present significant support for all hypotheses that were tested.

Lastly, the paired samples t-test was used to test whether perceived and (or) anticipated differences in issues to be considered exist regarding the context. The context difference analysis relates to the use of technology and its management requirements between the years 2019 and 2024. The paired-samples t-test was conducted on the results from the final round. From the issues identified from the literature, the results reveal 37.5% of the issues presented statistically significant support for a perceived shift in considerations. In contrast, the complement provided evidence that suggests otherwise. Similarly, a paired samples t-test was conducted on the issues the panellists raised. This t-test yielded just over 26.7% of the issues showing perceived and (or) anticipated shift in the context of the use of technology and its management for the time periods of interest.

Thus, the results suggest market preference analytics are an enabler of maximised plant utilisation through the design and operation of flexible manufacturing systems.

CHAPTER 5: DISCUSSION OF RESULTS

5.1 Introduction

This chapter discusses the results presented in Chapter 4, starting with the demographic profile of the panellists (5.2). Thereafter, the hypotheses test results are discussed (5.3). This is then followed by a discussion on validity and reliability (5.4). The chapter is closed with a conclusion of the discussion (5.5).

5.2 Demographic Profile of Panellists

The number of panellists for rounds one and two was sixteen (16) and thirteen (13), respectively. This panel size meets the minimum number of panellists required for valid Delphi Study results (Fink et al., 1984; Reid, 1988; Hasson, 2000; Thangaratinam & Redman, 2005; Sahari et al., 2018). As discussed in Chapter 4, various scholars suggest different minimum numbers of panellists for an acceptable Delphi Study cohort. Reid (1988) suggests ten (10) as the minimum number of panellists. In comparison, Thangaratinam and Redman (2005) suggest a minimum of four (4) panellists. Seven (7) or eight (8) panellists are suggested by Sahari et al. (2018). The suggested numbers are lower than the panellists for both rounds of this research; thereby, indicating the number of panellists for this study was acceptable.

The paired samples t-test results showed there was no statistical significance in the sample used between the two rounds of the Delphi Study. Moreover, the number of rounds were sufficient to generate adequate data for a Delphi Study (Starkweather, Gelwicks & Newcomer, 1975; Fink et al., 1984; Murphy et al., 1998; Melnyk et al., 2009).

All panellists who had participated in both rounds of the study had a tertiary education qualification at a minimum level of National Diploma, with the highest qualification at DPhil/PhD level. This education level spread meets the minimum requirement of knowledge. This requirement stems from research that attempts to define the traits of experts. The research is important as it centres on building expert opinion to increase the credibility of the results of a Delphi Study and other consensus techniques. The research on expert opinion builds credibility by attempting to measure the level of expertise of the panellists. Knowledge in the field under investigation is recommended as the key criterion when selecting a suitable “expert” panel (Sahari et al., 2018). Despite this view, Goodman (1987) presents evidence that shows “experts” do not necessarily have to be used in a Delphi study. Goodman (1987) proposes that informed advocates for a specific discipline or topic are adequately credible. Goodman (1987) argues stringent definitions of “expert” can breach the pragmatic nature of a Delphi Study and thereby dramatically reduce the number of reachable available experts (Goodman, 1987). The knowledge requirement of the panellists is met in this study, notwithstanding the view to relax the knowledge requirement proposed by Goodman (1987).

The spread in the distribution of the qualification levels of the panellists ensured that the feedback from the panellists, in round one, is vetted through a wide range of knowledge levels and backgrounds. The knowledge levels and backgrounds are based on the educational qualifications of the panellists. However, Bolger and Wright (1994) argue models-based definitions of professionalism and expertise are insufficient and propose experts should be determined by performance. Moreover, two main traits scholars appear to agree on emerge from the consulted literature when defining experts. These experts' traits from various research include the panellists' knowledge of and experience in their respective fields (Bolger & Wright, 1994; Shanteau et al., 2001, 2002b; Baker, Lovell & Harris, 2006).

To close the gap highlighted by Bolger and Wright (1994) and the emergent convergence on experience, three additional criteria were used to qualify the panellists' suitability for the study viz. industry; current position in the organisation and the number of years of experience. Firstly, the industries' spread had the majority representation of FMCG at 81% and 92% for rounds one and two, respectively. A small population of panellists followed this majority in ICT at 13% and 8% for the Delphi study's successive rounds. The lowest representation was pharmaceuticals at 6% for round one, which was not represented in the final round.

This distribution in the representation of industries was adequate to give credible performance-related opinions and insights into the supply chain as well as product lifecycle management work-processes. ICT experts' presence ensured that performance-based expert opinion and guidance on the proposed ICT constructs were elicited, specifically: on big data; market preference analytics; and related methodologies and technologies. Compared to those of other industries represented, the proportion of the ICT experts represented, although markedly less than FMCG representation, ensured that the study captured the investigated constructs' nuances and insights. The presence of ICT panellists was not overwhelming. Thus, ensuring the ICT experts' opinion would not have a more significant weight on the opinion of the investigated FMCG PLM and supply chain work processes' real performance.

Consequently, the ICT panellists' presence modulated the panellists' views from FMCG and Pharmaceutics industries on ICT expert issues. The ICT expert's light presence achieved the modulation effect because it also served to strengthen the arguments of the panellists who are advocates for ICT-based implements in the FMCG industries. These were panellists who were from the FMCG industry and are not ICT specialists. However, according to Goodman (1987), these panellists' opinions can be deemed credible as advocates of a particular view. The view, in this case, refers to advances in ICT technologies that could be applied in the FMCG industry.

Secondly, the consideration of the role of the panellists at their respective organisations indicates their performance as viewed by their colleagues. The perceived performance of expertise is linked to how the expert is valued in their respective roles by their colleagues in their organisation. This perception fulfils the requirements for *social acclamation* and *behavioural characteristics. Social acclamation* and *behavioural characteristics* relate to common recognition that one receives from professionals in a field (Shanteau et al., 2001), as discussed in Section 3.3 of this research report. The level of seniority of the role within an organisation typically requires the discharge of duties that demand higher performance.

For this reason, it can thus be reasonably expected that role level in an organisation gives an indication of the performance Bolger and Wright (1994) recommend should be used as a measure for performance-based expertise. Moreover, each role within an organisation has exposure to work-processes at tactical and (or) strategic level or in some combination of both levels (Thompson, Martin & Scott, 2017). This exposure and expertise of the panellists added credence to assessing the conceptual framework proposed in this research from a performance-based expert lens.

The panellists' roles in their respective organisations in this research were graded in the following order: junior management, middle management, functional specialist, senior management, and board of directors/c-suite/executive management. The grading used was sequenced to align with a typical organisation's tactical to strategic level configuration (Thompson, Martin & Scott, 2017). Although the panellists represented roles across an organisation's levels, both rounds' distribution spreads were right-skewed. This right-skewness in the roles' spread met the recommendation made by Murphy et al. (1998) for diversity in the panel. Murphy et al. (1998) suggest that a diverse panel leads to a diversity of views and a broad range of possible solutions. Additionally, the right-skewness in the panel's composition meets the recommendation made by Jairath and Weinstein (1994) on the latest available knowledge and perception. Moreover, the presence of junior managers and functional specialists satisfied the requirement of having amateur outsiders, whom Yousuf (2007) posit can better predict developments than established experts in a field.

The panel comprised of a majority of middle management level experts. These middle managers typically work with junior and senior management in organisations (Thompson, Martin & Scott, 2017). This exposure gives them access to both tactical and strategic work processes within their organisations (Thompson, Martin & Scott, 2017). Therefore, it can be expected that the panel would give more informed views on the interaction of these work processes. The middle managers would, therefore, give useful insights into the conceptual framework proposed in this research.

Lastly, the spread in the panellists' number of years of experience in their respective industries strengthened the accuracy of their predictions on the development of the investigated work processes (Yousuf, 2007). Yousuf (2007) highlights that future developments in a field are not accurately predicted by experts but by amateur outsiders' unconventional thinking. Between the two (2) rounds of the study, a minimum of 81% of the panellists comprised of experts with less than ten (10) years' of experience. The 81%

were made up of the lower majority of the two rounds at 63% of panellists with less than six (6) years' of work experience. Having a majority of panellists with less than six (6) years' of working experience aligns with and works into the study of the amateur recommendation as defined by Yousuf (2007). This amateur panel requirement is met because a typical organisation has more experienced experts occupying high-ranking roles that are strategic. Consequently, the high ranking experts' contribution to this study solidified the assessment of the validity of the feedback from their co-panellists. Moreover, it modulated for strategic applicability of the investigated conceptual framework's feedback.

In summary, the number of panellists in the two (2) rounds satisfied a Delphi Study's requirements. The diversity in education level, roles in the organisation and number of years of experience strengthened the validity and reliability of the panellists' opinions. Additionally, the panel composition had low years of experience linked to developmental views in work-processes. This low experience can account for the strong bias toward future organisational technology and operations. However, the presence of more senior experts in the panel balanced the overall opinions, thus modulating the expected bias in line with the Delphi Technique's design. This result strongly aligns with the Pragmatism worldview. The Pragmatism world-view is geared toward real-world practice, and this is embedded within the research design of this study (Creswell, 2014). Future studies can consider including participants who are not in the fields of direct interest to better match the recommendation by Yousuf (2007). Albeit, the recruits would have to be knowledgeable in the investigated PLM and supply chain work processes. The assessment results of the proposed linkages of the constructs within the work process covered in the conceptual framework are discussed in the next sub-section.

5.3 Hypotheses Testing: Conceptual Framework Constructs

The first objective of this research related to this section, in terms of the formulated hypotheses, is to validate the constructs of the proposed conceptual framework identified from the literature. Additionally, it is to fulfil the second research objective, which is to determine the linkages in the proposed conceptual framework that link big data to plant utilisation. Before discussing the results, it is essential to point out that the reliability and validity tests on the measurement of this scale (discussed in Chapter 3) proved satisfactory to address the research question in this respect. Thus, the results are based on a statically sound measurement basis through the Delphi Technique questionnaires administered online.

Next, the results for the hypotheses tests are discussed.

5.3.1 **Hypothesis 1 (H1) and Hypothesis 2 (H2)**: Big data is positively related to plant utilisation

This research report's objective as it relates to the hypotheses mentioned above was primarily to understand the data points available from big data and their influence on plant utilisation, H1. Secondarily, to understand the converse relationship from the influence of linking plant utilisation, in managing supply chain and PLM, to big data, H2. Before discussing the results, it is imperative to point out that the reliability and validity tests on the measurement of this scale (as discussed in Chapter 3) proved appropriate to address the research question in this regard. Thus, the results are based on sound statistical measurement bases through the Delphi Technique questionnaires administered online.

Big data relates to voluminous, scattered, and unstructured data as it occurs on ICT platforms(Rozados & Tjahjono, 2014; Yin & Kaynak, 2015; Jin et al., 2016). In this data, there is demand data. Which then branches into demand management data and product development data (Stone, 1980; Johns & Pine, 2002; Hussain et al., 2013; Jin et al., 2015), as discussed in Chapter 1. Further, as discussed in Chapter 2, there are three sub-constructs of demand management and product management data within the big data construct. The constructs consist of (1) consumer opinion data, (2) consumer behaviour data, and (3) equipment management data (Albert, Tullis & Tedesco, 2010; Netzer et al., 2012; Johanson et al., 2014; Culotta & Cutler, 2016; Jin et al., 2016; Nam, Joshi & Kannan, 2017; Zhang, Ren, Liu, Sakao, et al., 2017; Tao et al., 2018). Subconstruct (1) and (2) are market preference sources, while subconstruct (3) is data sourced from plant equipment performance.

The plant utilisation construct, for demand management (Croxton et al., 2002), as discussed in Chapter 1, relates to the performance metric that accounts for factors that influence planned production time viz. (1) legal non-operating time, (2) plant shutdown due to maintenance, and (3) product orders (Muchiri & Pintelon, 2008). This metric is of significance because it gives an indication of the financial viability of investments made on plants that are recoverable (Sinnott et al., 2006). Consequently, equipment management data, collected through the internet of things, IoT, and artificial intelligence, AI, presents information about the capacities, performance and state/condition of the equipment are sub-constructs to the plant utilisation construct. As literature presented in Chapter 2 of this research report shows, the data sources for this construct include ICT platforms, PEIDs, and sensors (Lee, Bagheri & Kao, 2015; Wang et al., 2017; Zhang, Ren, Liu, Sakao, et al., 2017; He & Wang, 2018; Tao et al., 2018). As shown in Chapter 4, the results with respect to big data and plant utilisation suggest a positive significant relationship, as expected, based on literature. Therefore, the results present significant support for Hypothesis 1 and Hypothesis 2.

The results regarding a significant relationship between big data and plant utilisation are congruent with the literature in this domain. Incumbent systems use data collection and analysis mechanisms that are mostly not integrated and arguably inefficient at enabling the effective management of supply chain and PLM work processes in a holistic manner (Crawford, 2011; Zhou, Ji & Jiao, 2013; Mourtzis & Doukas, 2014). 4IR functionalities enable handling massive volumes of data generated from various sources at high velocities, *inter alia* (Rüßmann et al., 2015). These functionalities further present the market preference analytics, including equipment management data (Li et al., 2015; Rüßmann et al., 2015), in formats that can support decision making, thus, empowering manufacturers with holistic information (Mourtzis & Doukas, 2014; Nguyen et al., 2018). Based on this information, manufacturers can make decisions that lead to strategic positions. Subsequently, the strategic positions can lead to competitive advantages (Porter, 1996) due to improved supply chains as well as PLM designed and operated for maximised plant utilisation.

Based on the study presented above, Hypotheses 1 and 2: big data is positively related to plant utilisation, is significantly supported. This outcome suggests there are mutual benefits between big data and maximised plant utilisation.

5.3.2 **Hypothesis 3 (H3)**: Big data is positively related to consumer preferences

This research report's objective as it relates to the hypothesis mentioned above was to understand how big data influences consumer preferences, H3. It is important to point out that the reliability and validity tests on the measurement of this scale (as discussed in Chapter 3) proved appropriate to address the research question in this regard. Thus, the results are based on sound statistical measurement bases through the Delphi Technique questionnaires administered online.

The sub-constructs of big data pertinent to this research are discussed in Section 5.3.1, with a more detailed discussion in Chapters 1 and 2. The construct of consumer preferences relates to a product's intrinsic and extrinsic properties (Symmank, 2019). These preferences capture the ”likes, dislikes, motivations and inclinations that drive purchasing decisions” and consumer behaviour (Spacey, 2017, paras 2–11), as discussed in Chapters 1 and 2. As shown in Chapter 4, the results with respect to big data and consumer preferences suggest a positive significant relationship, as expected based on literature. Therefore, the results present substantial support for Hypothesis 3.

The results regarding big data and consumer preferences having a significant relationship are congruent with the literature in this domain. Works done by Nam, Joshi and Kannan (2017) and Culotta and Cutler (2016) on brand perceptions provide evidence that big data do contain consumer opinion that yields consumer preferences from the data mining methodologies explored in their respective works. Primary data are presented by Nam, Joshi, and Kannan (2017), and it includes questionnaires as well as surveys. Text mining as a tool used to extract consumer preferences is presented by Lee and Bradlow (2011), Netzer et al. (2012), and Tirunillai and Tellis (2014). Social tags are advocated for by Nam, Joshi and Kannan (2017) as a method showing great promise and with comparable outcomes to the more established methods. All three methods are used to extract data from various sources discussed in Chapter 2. Another source of consumer preferences, discussed in Chapter 2 of this research report, is based on data collected from product embedded information devices (Johanson et al., 2014; Zhang, Ren, Liu, Sakao, et al., 2017). The information collected by PEIDs gives information on how a product interacts with the product during its lifecycle. This information is thus consumer behaviour data (Johanson et al., 2014). Apart from work on PEIDs, the complement of the works provides evidence of the successes of the afore-mentioned methods in practice, this further supports the results reported herein.

Based on the study presented above, Hypothesis 3: Big data is positively related to consumer preferences, is significantly supported. This outcome suggests big data contains consumer preferences.

5.3.3 **Hypothesis 4 (H4)**: Consumer preference data are positively related to product development

This research report's objective as it relates to the hypothesis mentioned above was to understand the effect of consumer preferences on product development. Prior to discussing the results, it is important to point out the reliability and validity tests on the measurement of this scale (as discussed in Chapter 3) proved appropriate to address the research question in this regard. Thus, the results are based on sound statistical measurement bases through the Delphi Technique questionnaires administered online.

The consumer preference construct is as described in the preceding sub-section 5.3.2 of this chapter, with detailed discussions in Chapters 1 and 2 of this research report. The product development construct relates to the process of determining product attributes from consumer preferences. The product attributes are subsequently optimised to find optimal product architectures and families. Also, within this construct are considerations of the mass customisation limitations that are factored into the optimisation of product architectures and families, as discussed in Chapter 1 and 2. As shown in Chapter 4, the results in respect of consumer preferences and product development suggest a positive significant relationship. This outcome was expected based on the literature reviewed. Therefore, the results present substantial support for Hypothesis 4.

The results regarding consumer preferences and product development having a significant relationship are congruent with the literature in this domain, as well. Yin and Kaynak (2015) and Wang et al. (2017) assert consumer preferences can lead to new product development. Koen (2004) states that consumer preferences can lead to three main product development types. These product types are breakthrough, platform and incremental products (Koen, 2004). It is important to note the approach of extracting product attributes from consumers is not novel because it has been widely used in product development. Traditional approaches have only considered the consumer preferences after the product has been manufactured (Zhou, Ji & Jiao, 2013). This is works on feedback-based design. The novelty, and contribution of this research is in using big data as a source of consumer preferences and equipment management data for specifically proactively improving the design as well as operation of the PLM and supply chain work processes in the FMCG industry.

Based on the study presented above, Hypothesis 4: Consumer preference data are positively related to product development, is significantly supported. This outcome suggests that consumer preferences from big data promote product development.

5.3.4 **Hypothesis 5 (H5)**: Product development is positively related to process parameters in manufacturing

This research report's objective as it relates to the hypothesis mentioned above is to understand the effect of product development on process parameters. Prior to discussing the results, it is important to point out that the reliability and validity tests on the measurement of this scale (as discussed in Chapter 3) proved appropriate to address the research question in this regard. Thus, the results are based on sound statistical measurement bases through the Delphi Technique questionnaires administered online.

The product development construct is as described in the preceding sub-section 5.3.3 of this chapter, with detailed discussions in Chapters 1 and 2 of this research report. The conversion of preferences to process parameters construct, as the name suggests, relates to the process of converting consumer preferences into process parameters. This stage's consumer preferences relate to the optimised product attributes from the optimised product architectures and families that would have been identified in the preceding construct of product development, as discussed in Chapter 1. As shown in Chapter 4, the results in respect to product development and conversion of preferences to process parameters suggest a positive significant relationship, as expected, based on the literature reviewed. Therefore, the results present substantial support for Hypothesis 5.

The results regarding product development and conversion of preferences to process parameters having a significant relationship are congruent with the literature in this domain. Jin et al. (2016) present evidence that the quality function deployment, QFD, is criticised for its inability to balance the importance of customer requirements, CRs. The inability of the QFD necessitates that it is used with the analytic hierarchical process, AHP, to balance the importance of CRs (Jin et al., 2016). Further, Li et al. (2015) suggest the approach needs to evolve to manage the intricate correlations between function and needs. New approaches have been developed, including QCC, ISO 9000, TQM, etc., to improve consumer satisfaction (Sauerwein et al., 1996; Kondo, 2001) and loyalty (Zhu et al., 2010), as discussed in Chapter 1. This developmental work in the domain of quality management systems indicates the importance of and the shift towards the improved capture of consumer preferences for the final product ahead of its manufacture. This improved capture of preferences is pursued by ensuring the process parameters are determined and finalised while embedding them within the product lifecycle and supply chain work processes. Doing so is attractive to and pursued by manufacturers who want to remain competitive because it leads to competitive advantage (Porter, 1996).

Based on the study presented above, Hypothesis 5: product development is positively related to process parameters in manufacturing, is significantly supported. This outcome suggests that product development from big data promotes the conversion of preferences to process parameters.

5.3.5 **Hypothesis 6 (H6)**: Process parameters are positively related to mass customisation in terms of the manufacturing equipment design and optimisation

This research report's objective as it relates to the hypothesis mentioned above is to understand the effect of process parameters on mass customisation in terms of equipment design and optimisation. Prior to discussing the results, it is pertinent to point out that the reliability and validity tests on the measurement of this scale (as discussed in Chapter 3) proved appropriate to address the research question in this regard. Thus, the results are based on sound statistical measurement bases through the Delphi Technique questionnaires administered online.

The process parameters construct is as described in the preceding sub-section 5.3.4 of this chapter, with detailed discussions in Chapters 1 and 2 of this research report. The mass customisation construct relates to the competitive means that leverage high process flexibility and integration to provide each consumer with personalised products (Da Silveira, Borenstein & Fogliatto, 2001), at efficiencies competitive to those of mass production (Kotler, 1989). As discussed in Chapter 1 in this report, mass customisation refers to the design and optimisation of equipment. The intent of the design and optimisation stage is to meet the outcomes of high process flexibility and integration to deliver personalised products to consumers at high efficiencies, in line with the definitions tendered by Da Silveira, Borenstein, and Fogliatto (2001) and Kotler (1989). As shown in Chapter 4, the results in respect of conversion of preferences to process parameters and mass customisation, suggest a positive significant relationship, as expected, based on the literature reviewed. Therefore, the results present substantial support for Hypothesis 6.

The results regarding a significant relationship between process parameters and mass customisation are congruent with the literature in this domain. Wang et al. (2017) assert that in MC, consumer interaction facilitates product design and manufacturing. As discussed in Chapter 2, Wang and Tseng (2011) highlight the shortfall of the online-configuration model as limiting the consumer's choices to predetermined options. While Zhang et al. (2017) highlight the alternative, i.e. embedded toolkits for co-creation typically used in MC overcome the shortfall of the online-configuration toolkit. However, the shortfall is the embedded toolkit's flexibility which can result in complex product and (or) financially unfeasible designs (Zhang, Ren, Liu, Sakao, et al., 2017). Future work should be geared towards design methods that are specific data-driven (Zhang, Ren, Liu, Sakao, et al., 2017). This developmental work in mass customisation and its requirement for refined processes to manage the consumer requirements as well as manufacturers' limitations remains an area of growing interest.

Based on the study presented above, Hypothesis 6: process parameters are positively related to mass customisation in terms of the manufacturing equipment design and optimisation, is significantly supported. This outcome suggests product development from big data promotes the conversion of preferences to process parameters.

5.3.6 **Hypothesis 7 (H7) and Hypothesis 8 (H8)**: Product development is related to mass customisation (in terms of the manufacturing equipment design and optimisation)

This research report's objective as it relates to the hypotheses mentioned above was first to understand the impact of mass customisation on product development, H7. Secondly, to understand the influence of product development on mass customisation, H8. Before discussing the results, it is imperative to point out that the reliability and validity tests on the measurement of this scale (as discussed in Chapter 3) proved appropriate to address the research question in this regard. Thus, the results are based on sound statistical measurement bases through the Delphi Technique questionnaires administered online.

The process development construct is as described in the preceding sub-section 5.3.3, with detailed discussions in Chapters 1 and 2 of this research report. Whereas the mass customisation construct is as described in the preceding sub-section 5.3.5, with detailed discussions in Chapters 1 and 2 of this research report. As shown in Chapter 4, the results concerning product development and mass customisation suggest a positive significant relationship, as expected, based on the literature reviewed. Therefore, the results present substantial support for Hypotheses 7 and 8.

The results regarding product development and mass customisation having a significant relationship are congruent with the literature in this domain. Labbi, Ouzizi and Douimi (2015) propose supply chain constraints be worked into the product design process and vice versa. Khan, Christopher and Creazza (2012) posit that doing so leads to competitive advantages and resilient supply chains. Novak and Eppinger (2001) are proponents of optimising product attributes simultaneously with the supply chain structure. Nepal et al. (2012) posit product design and supply chain should be loaded at the front end of product development. This body of work provides evidence of the successes of the afore-mentioned methods in practice; this further supports the results.

Based on the study presented above, Hypotheses 7 and 8 Product development is related to mass customisation (in terms of the manufacturing equipment design and optimisation) are significantly supported. This outcome suggests product development and mass customisation as it relates to the manufacturing design and optimisation are interdependent.

5.3.7 **Hypothesis 9 (H9)**: Mass customisation (equipment design, including its optimisation) is positively related to flexible manufacturing systems

This research report's objective as it relates to the hypothesis mentioned above is to understand the effect of mass customisation in terms of equipment design and optimisation on flexible manufacturing systems. Prior to discussing the results, it is important to point out that the reliability and validity tests on the measurement of this scale proved appropriate to address the research question in this regard. Thus, the results are based on sound statistical measurement bases through the Delphi Technique questionnaires administered online.

The mass customisation construct is as described in the preceding sub-section 5.3.5 of this chapter, with detailed discussions in Chapters 1 and 2 of this research report. The flexible manufacturing systems construct relates to routing and machine flexibilities (Yildirim & Yücel, 2016; Mahmood et al., 2017). As discussed in Chapters 1 and 2 of this research report, routing flexibility refers to a system's modifiability to produce new products. Whereas machine flexibility refers to multiple machines' ability to carry out the same operation on a part (Shang & Sueyoshi, 1995; Al-Kahtani et al., 2014; Yildirim & Yücel, 2016). This construct's function uses the mass customisation design and optimisation outputs, then commissions them for operations (Shang & Sueyoshi, 1995; Al-Kahtani et al., 2014; Yildirim &

Yücel, 2016). The capabilities of flexible manufacturing systems are leveraged to deliver mass customised products at efficiencies competitive to those of mass production. As shown in Chapter 4, the results with respect to mass customisation and flexible manufacturing systems suggest a positive significant relationship, as expected, based on the literature reviewed. Therefore, the results present substantial support for Hypothesis 9.

The results regarding mass customisation and flexible manufacturing systems having a significant relationship are congruent with the literature in this domain. Shang and Sueyoshi (1995), Al-Kahtani et al. (2014), Yildirim and Yücel (2016) propose that flexible manufacturing systems are best suited to address the constantly changing consumer needs. This based on the inherent flexibilities these systems possess, which allow them to accommodate the requisite operational changes dictated by continually changing consumer needs and preferences. Al-Kahtani et al. (2014) suggest flexible manufacturing systems can fulfil mass customisation requirements. Shafiq, Faheem and Ali (2010) purport this is enabled by the flexibility types that can be derived for flexible manufacturing systems.

Based on the study presented above, Hypothesis 9: mass customisation (equipment design, including its optimisation) is positively related to flexible manufacturing systems. This outcome suggests that mass customisation promotes flexible manufacturing systems.

5.3.8 **Hypothesis 10 (H10)**: Flexible manufacturing systems are positively related to plant utilisation

This research report's objective as it relates to the hypothesis mentioned above is to understand the effect of flexible manufacturing systems on plant utilisation. Prior to discussing the results, it is important to point out that the reliability and validity tests on the measurement of this scale proved appropriate to address the research question in this regard. Thus, the results are based on sound statistical measurement bases through the Delphi Technique questionnaires administered online.

The flexible manufacturing systems construct is as described in the preceding sub-section 5.3.7 of this chapter, with detailed discussions in Chapters 1 and 2 of this research report. The plant utilisation construct is as described in the preceding sub-section 5.3.1 of this chapter, with detailed discussions in Chapters 1 and 2 of this research report. As shown in Chapter 4, the results with respect to flexible manufacturing systems and plant utilisation suggest a positive significant relationship, as expected, based on the literature reviewed. Therefore, the results present substantial support for Hypotheses 10.

The results regarding a significant relationship between flexible manufacturing systems and plant utilisation are congruent with the literature in this domain. Performance analyses carried out by El-Tamimi et al. (2012), and Mahmood et al. (2017) in their respective works show flexible manufacturing systems improve plant utilisation among other performance measures. Further evidence is presented by Al-Kahtani et al. (2014), who assert flexible manufacturing systems installations have yielded improvement in: capital utilisation (thus plant utilisation); increased profit margins; and competitive advantage, as discussed in Chapter 2 of this research report.

Based on the study presented above, Hypothesis 10: flexible manufacturing systems are positively related to plant utilisation. This outcome suggests that flexible manufacturing systems promote high plant utilisation.

5.3.9 **Hypothesis 11 (H11) and Hypothesis 12 (H12)**: Consumer preferences are related to mass customisation in terms of the manufacturing equipment design and optimisation

This research report's objective as it relates to the hypotheses mentioned above was first to understand the impact of mass customisation on consumer preferences, H11. Secondly, to understand the influence of consumer preferences on mass customisation, H12. Before discussing the results, it is imperative to point out the reliability and validity tests on the measurement of this scale proved appropriate to address the research question in this regard. Thus, the results are based on sound statistical measurement bases through the Delphi Technique questionnaires administered online.

The consumer preferences construct is as described in the preceding sub-section 5.3.1, with detailed discussions in Chapters 1 and 2 of this research report. Whereas the mass customisation construct is as described in the preceding sub-section 5.3.5, with detailed discussions in Chapters 1 and 2 of this research report. As shown in Chapter 4, the results with respect to product development and mass customisation suggest a positive significant relationship, as expected based on literature. Therefore, the results present substantial support for Hypotheses 11 and 12.

The results regarding a significant relationship between product development and mass customisation are congruent with the literature in this domain. Labbi, Ouzizi and Douimi (2015) propose supply chain constraints be worked into the product design process and vice versa. In mass customisation, this outcome is pursued through value co-creation toolkits viz. online configuration toolkits and the embedded toolkits (Zhang, Ren, Liu, Sakao, et al., 2017). These value co-creation toolkits are used to directly elicit consumer preferences (Zhang et al., 2017) within the manufacturing capabilities' limitations. The resultant output from using these toolkits are product designs informed by consumer preferences and manufacturing constraints. This interplay of consumer preferences and manufacturing constraints contributes to the parameters that can be used during the optimisation stages of manufacturing systems design. The optimisation of the manufacturing systems can lead to reduced manufacturing costs and increased value for the consumer.

Based on the study presented above, Hypotheses 11 and 12 consumer preferences are related to mass customisation in terms of the manufacturing equipment design and optimisation. This outcome suggests product development and mass customisation in terms of manufacturing design and optimisation are interdependent.

5.3.10 Conclusion of Hypotheses Testing

In summary, experts agree big data can be used as a source of market preference analytics to maximise plant utilisation, leading to the design and operation of flexible manufacturing systems in the FMCG industry. The expert panel has validated the constructs and relationships identified from the literature reviewed that have been included in the conceptual framework. The hypothesis test results have fulfilled the first and second objectives of this study. In the next section, the results relating to the third objective of this research are discussed.

5.4 Validity

5.4.1 Internal Validity

The outcomes of the hypotheses tests are validated in the measures of central tendencies, which are commonly used to measure consensus in Delphi Studies (Hasson, 2000; Schmidt et al., 2001; Akkermans et al., 2003; Ogden et al., 2005; Thangaratinam & Redman, 2005; Yousuf, 2007; Melnyk et al., 2009; Giannarou & Zervas, 2014; Hsu & Sandford, 2015). As depicted in Table 4.5, there was a strong consensus amongst the experts on constructs and proposed conceptual framework's respective proposed links. This consensus showed the median's convergence; it was reached as early as round one (1). The converged consensus was evident in the decreased spread in the opinions, as seen in the IQR, of round two. This reduction in the spread can mean the panellists had learned from each other in the first round’s feedback. This learning effect, according to Sackett et al. (1996), Murphy et al. (1998) and Schmidt et al. (2001), shows internal validity and reliability for the conceptual framework.

Internal validity (credibility) concerns the ability to draw correct inferences about the population from the data (Leedy & Ormrod, 2015). Internal validity further indicates the legitimacy of the results of the study as determined by the manner in which the participants were selected, and data were recorded, or analyses were conducted (Mohajan, 2017). Validity is addressed by Murphy et al. (1998), suggesting it can be achieved through:

i. comparison against a standard, e.g. using the results of a randomised-controlled trial's results that are not disclosed to the Delphi panellists.
ii. using criterion-related (predictive and concurrent) validity by comparing the inquiry results with results from other sources.
iii. Evaluating the logic of the group, e.g. testing the spread of the responses for a common situation
iv. Evaluating the face validity, Havins (2006) suggests the following questions: "Do intended users understand the design? Does it make sense to them? Do they appreciate the implications of comparing program A with Program B? Do they know what the design includes, or does it not include, in a control group? Is the sample size sufficiently large to be believable?"

In this study, criteria (iii) and (iv) are found appropriate and used. Validity test through criterion (iii) evaluation of the group's logic is achieved through the IQR results from the Delphi Technique questionnaire. Criterion (iv) face validity is achieved through the design and the procedure followed in conducting the Delphi Technique for this research which is in line with Delphi Studies from the consulted literature.

Moreover, evident across all the tested linkages is that the difference in mean was positive, except for question one (1), due to the learning effect. A positive difference in mean between rounds one (1) and two (2) indicates an increase in the mean on a topic. An increase in mean indicates a link had moved from a rating that is skewed toward "slightly possible" to one that is closer to "significantly possible." In the case of question one (1), there was a minor reduction in the level of confidence on the proposed link. The Delphi Study results are consistent with the literature discussed in Chapters 1 and 2 of this report to formulate each hypothesis in detail.

5.4.2 Ecological Validity

This study's third and final objective is to determine the impact of consumer preferences on the equipment design and how these consumer preference data affect the design constraints. Results presented in Table 4.6 show consensus and IQRs of 0 and 1 on the rated issues. These issues were identified from literature that relate to how consumer preferences and other insights derived from big data can be worked into the supply chain and product lifecycle management work-processes.

Additionally, covered in this section is the consideration of ecological validity. Ecological validity concerns generalising research results to well-defined target populations, organisations, contexts, or time (Drost, 2011; Bhattacherjee, 2012). In this research, the proposed conceptual framework's ecological validity is assessed against the present technological era within the time-frame of 2019 and 2024 in the FMCG industry.

Manufacturing technologies are designed based on natural principles across different industries. Despite this fact, the shorter shelf lives often encountered in FMCG industries made the question of ecological validity of keen interest in this research. It is subsequently answered in the results section. Literature consulted for this research can lead one to expect this research's proposed conceptual framework is likely to apply to industries that make products with longer lead times to market. This expectation can be backed by the ubiquitous research on equipment management data, PEID and flexible manufacturing systems. The widely occurring research on these topics has been conducted in mostly foundry-like manufacturing for automotive industries, as discussed in Chapter 2 of this research report. However, the panellists agree the conceptual framework can be applied in the FMCG industry. This view suggests the conceptual framework can be applied with success in South Africa.

The time aspect of ecological validity is approached by looking at (i) the importance level placed on the identified constructs from literature and issues based on the time frames of 2019 and 2024 and (ii) at the level of consensus on each issue. These proved to be consistently high as well as consistent with expectations. One could expect the technology advances would require more resource investment over time as big data analytics technology gets adopted into industries. This expectation is in line with the technology adoption cycle, as depicted in Figure 5.1.

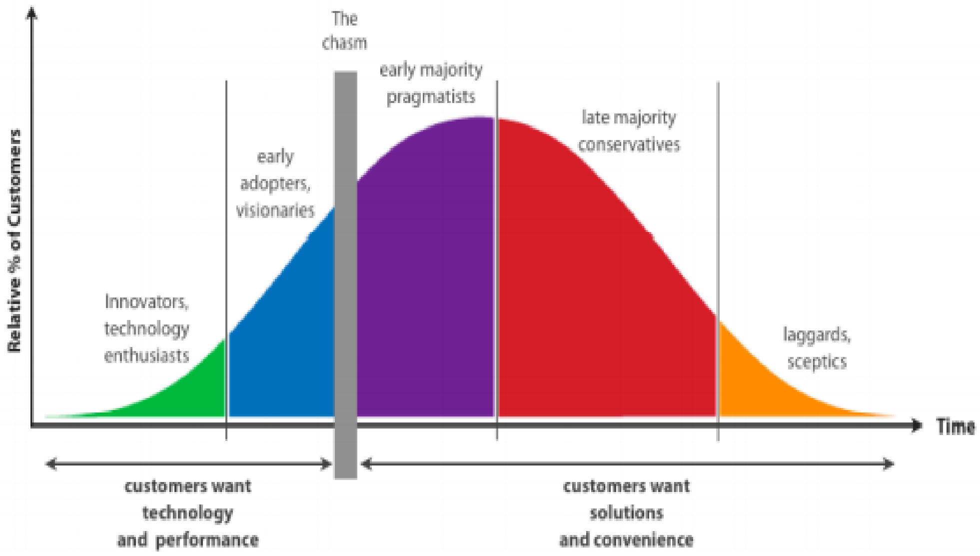

Figure 5.1: Technology Adoption Cycle. <u>Source:</u> du Preez et al. (2015: 32)

The expectation is that there would be a marked increase in the capabilities required to both operate and manage the technology as it matures and penetrates the market. This period aligns with the technology's expectations becoming clearer and exceeded (du Preez et al., 2015). This period is also the period in which early adopters and visionaries adopt the technology. As industries meet these requirements, while they adopt the technologies, more application opportunities will become evident. These application opportunities, in themselves, will result in more managerial oversight capabilities being required. As analytics technology matures, the early majority pragmatist(s) will adopt the technology with the least resource demand experienced at the stage when laggards and sceptics adopt (du Preez et al., 2015). The results in Chapter 4 are consistent with this expectation. Even though this view is consistent with theory, it should be approached with caution because significant changes can occur within the time frame considered in this research. The developments within this time frame could disrupt the advances made in a progressive or regressive manner.

The final point of validation of the conceptual framework proposed in this research report is seen in the issues suggested by the panellists. The number of these issues raised by the panellists, as additional considerations, for the management requirements of the technologies proposed in the conceptual framework further legitimise this research's results. The results suggest the proposed conceptual framework, which links big data to maximised plant utilisation, is valid. Furthermore, the additional considerations, coupled with the consensus level reached within one round, further confirm the conceptual framework is valid. Moreover, the panellists' concerns suggest big data will require the industry to reconsider strategic and tactical management for the technology it adopts.

5.5 Summary of Discussion

In summary, the expert panellists viewed market preference as having a positive impact on plant utilisation. They perceived market preferences would, in fact, lead to flexible manufacturing systems in the FMCG industry.

Most noteworthy in the panellists’ view is the technologies and improvements proposed in this research can be adopted in the FMCG industries to improve the supply chain and product lifecycle management work-processes. This view is important because the literature shows extant research on flexible manufacturing systems has been conducted in other industries and not in FMCG. The panellists further validated the proposed conceptual framework can be applied. The framework can be applied in using big data to source market preference analytics to design and operate flexible manufacturing systems to achieve maximum plant utilisation.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter commences with the general and hypothesis specific conclusions drawn from the study, together with contributions made by this research (6.2). This is followed by the recommendations (6.3) and suggestions for future research (6.4).

6.2 Conclusions of the Study

This study sought to determine how a framework linking market preference analytics linked to FMS leads to maximised plant utilisation in the FMCG's industry can be developed. The Delphi technique was used to develop and validate to assess a proposed conceptual framework. The Delphi Technique is appropriate for this outcome because it is a proven research mechanism used to build the basic elements of a phenomenon (Meredith et al., 1989; Habibi, Sarafrazi & Izadyar, 2014) and pre-empting the structure of a model (Turoff & Linstone, 2002). A framework of this nature is necessary because of the big data generated by consumers; big data analytics; and advances in manufacturing technology create new strategic positioning opportunities for manufacturers. These strategic positions opportunities offer manufacturers more benefits and are a departure from operational effectiveness programs, aiming to improve manufacturing capacity (Porter, 1996).

The pursuit of the considered framework led to the objectives of this research which are to:

(i) Determine the constructs in the framework for using big data to improve utilisation.
(ii) Determine how big data can be linked to plant utilisation.
(iii) Determine the impact of consumer preference(s) on the equipment design and how consumer preferences data affect the design constraints.

These objectives were fulfilled by identifying the constructs that are relevant to the framework from the extant literature. In this study, a conceptual framework was proposed based on literature that links big data to maximised plant utilisation to address these objectives. Additionally, the validity of the constructs and linkages were tested through the Delphi Technique. This framework was constructed by connecting the product design sub-process to the supply chain and product sub-processes lifecycle management work-processes viz. product design, manufacturing and distribution. These linkages were tested through twelve (12) hypotheses. The results from all the tested hypotheses suggest statistically significant supported relationships at a significance level of $\alpha = 0.05$. Therefore, it can be concluded that the linkages on the proposed framework are significant.

Several conclusions are drawn based on this study's empirical findings and existing theory. Additionally, contributions are noted from the study, where such findings differ from findings in the literature.

6.2.1 Conclusions and contributions – Hypotheses

Based on this study, although other conclusions can be drawn; it can be concluded that using market preference analytics to maximise plant utilisation leads to FMS in the context of the Fast Moving Consumer Goods industry.

This study has further strengthened the emerging research incorporating product characteristics extracted from consumer big data into the supply chain design and operation. Studies in this particular context are limited; therefore, this study complements the literature and presents further research areas.

Additionally, this study complements literature on frameworks that integrate the supply chain and product lifecycle management work-processes, including Rozados and Tjahjono (2014), Li *et al*. (2015) and Nguyen *et al*. (2018). It extends the frameworks provided in the cited works' data sources to include market preferences from big data. This extension builds a balanced focus on manufacturers' external (i.e., through market preference analytics) and internal information sources (i.e., equipment management data). Thus, the proposed framework promotes a holistic perspective on managing supply chain and product lifecycle management work-processes, more importantly, in the FMCG industry.

6.2.2 Limitations

The study's main limitation is the practicality discussed in sub-section 3.6, also noted by Jones, Sanderson and Black (1992) and Powell (2003).

Further limitations:

(i) The sample size was small and restricted the use of advanced statistical analyses to make statistically significant inferences,

(ii) Convenience sampling does not allow every possible respondent equal opportunity from the population; this is a source bias.

(iii) Big data can give insights to product designs that consumers are not consciously aware they are designing. This unintentional design may lead to designs that consumers do not relate to at face value and may need further persuasion to consume.

(iv) Limitations inherent with the research methodology. The main limitation being practicality, i.e., panellist retention with possible low participation rates for the Delphi study's successive rounds. The second limitation is the generalisability of the findings from a Delphi study. As noted in Chapter 3, the Delphi Technique outcomes do not earn reliability and validity from statistical bases but rather from the merits of the panellists and their collective judgement. In this research, the panellist dropped from sixteen (16) in the initial round to thirteen (13) in the final round. Despite this drop-out rate, this study meets the minimum proposed in the literature (refer to Chapter 3).

6.3 Implications and Recommendations

This sub-section concerns implications and recommendations for government, practitioners and academia.

6.3.1 Government

Based on this study, consideration of the ethics and security related to data sourced from an individual's ICT platforms should be a high priority for the government. This requirement prompts legislation on and enforcement of sensitive personal information protections, including intellectual properties in data flows between individuals and manufacturers. Big data changes the creative landscape because it can carry an individual’s intellectual flows and knowledge structure. These aspects of big data thus require ongoing monitoring of the regulations and environment.

6.3.2 Practitioners

The results of this study provide valuable information to manufacturers in the FMCG industry. This information could inform strategies to capitalise on the benefits of using big data for product and supply chain design as well as operations. However, it is also advisable that each manufacturer should conduct its own analyses to understand the return on investment from adopting this proposed approach.

6.3.3 Academia

The dynamism of knowledge creates an environment for academics to interrogate evolving contexts. This view is justified by the pragmatism world-view embedded in this study, which is based on the “what” and “how” of knowledge. The question arises whether the same processes confirmed by this research are universally applicable or are they confined to specialised contexts, e.g. Brazil, Middle East, and (or) Europe, and the times?

6.4 Suggestions for Future Research

Future research can build on this study, big data, the supply chain, and product lifecycle management work-processes. The following significant opportunities for future research are:

(i) Research with a statistically significant sample size to validate the findings of this study
(ii) Determination of how unguided big data for in elicitation of market preferences for product development and (-or) manufacturing design and operation compares to guided elicitation of market preference analytics data
(iii) Determine how market preference analytics can be integrated into the design of the distribution and product disposal constructs within product lifecycle management and supply chain work-processes
(iv) Develop mechanisms that can be employed to assist the regulation of data flows between individuals and manufacturers in creating a secure information environment
(v) Determine the capability required for the human and technological resources in business.

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APPENDIX A-ETHICS CLEARANCE COMMUNICATION

Khanyiso Vuyelwa

From:	Bruno Emwanu <Bruno.Emwanu@wits.ac.za>
Sent:	12 November 2019 12:52 PM
To:	William Vuyelwa
Cc:	Raj Siriram
Subject:	Vuyelwa William ethics clearance number

Dear William,

I am pleased to inform you that the School Ethics Committee has completed assessing your ethics application for your MSc 50/50 research and clearance has been provided. You may now begin data capture and the rest of the research.

The ethics clearance number for your research report is MIAEC 238/19

Please use your ethics clearance number as a reference for all future correspondence on this matter.

By copy of this email, your supervisor is also informed.

Regards,

Dr. Emwanu

APPENDIX B - PANELLIST INFORMATION SHEET AND CONSENT FORM

DELPHI STUDY INFORMATION SHEET

We would like to invite you to take part in a Delphi consensus study. Before you decide whether you would like to take part or not, it is important for you to consider why the study is being done and what it will involve.

Please read this information sheet carefully.

What is a Delphi study?

The Delphi technique seeks to obtain consensus on the opinions of experts, termed panel members, through a series of structured questionnaires. As part of the process, the responses from each round are fed back in summarised form to the participants who are then given an opportunity to respond again to the emerging data. The Delphi is therefore an iterative multi-stage process designed to combine opinion into group consensus.

What is the purpose of the study?

Common practice in product development does not consider the voice of the consumer at design phase of product development but after manufacturing at product evaluation phase (QResearchSoftware.com, n.d.; Zhou, Ji & Jiao, 2013). This coupled with consumer feedback from surveys, focus groups and questionnaires is aggregated information, which leaves out some information, outliers, that could present further market penetration opportunities. Often the feedback from this approach translates to incurring high costs to modify the supply chain, the manufacturing process included, to meet consumer preference and demand. Big data contains a lot of information on consumers, generated and stored electronically and is available to manufacturers. The study aims to establish a framework that links big data with flexible manufacturing system design that can be used to maximise manufacturing plant utilisation.

The study also hopes to establish this framework through expert consensus. The objectives of this study are to:

iv. determine the constructs to be included in the framework for using big data to improve utilisation
v. determine the impact of customer preferences on the equipment design and how the consumer preference data affect the design constraints
vi. determine how big data can be linked to plant utilisation.

Why have I been invited to take part?

As an established expert in this field we are keen to gain your views about which variables may be important in product development from big data. We plan to recruit 15-20 participants consisting of data scientists, product development and process engineers together with selected experts in marketing, manufacturing and supply chain management.

What will I be asked to do if I take part?

We are inviting you to participate as a Delphi panel member. This would involve completing a brief questionnaire using an online survey. It is envisaged that this should take approximately 30. You would subsequently receive a reminder of your ratings, a summary of the group's responses and a further online questionnaire to re-rate the original list of identified factors. This process would continue until a group consensus is achieved or three Delphi rounds have been completed. In order to allow timely conclusion of the study we would respectfully request a response time of 1 week for completion of each round.

Who is organizing and funding the research?

This study is carried out in fulfilment of the requirements for a Master of Science degree in Engineering.

The Delphi study will be conducted by Mr Khanyiso Vuyelwa, a Process Engineer at a manufacturing plant and a student at the University of the Witwatersrand, and supervised by Professor Raj Siriram, University of Witwatersrand.

Potential Risks

The risks associated with participation in this study are minimal. If you should feel uncomfortable about participating in the Delphi Study, you can discontinue study participation at any time without repercussions by clicking the link asking you to be removed from the mailing list. All data collected will be stored in a password-protected computer file in the Principal Investigator's computer available only to the Principal Investigator.

Potential Benefits

There are no direct benefits to participants. However, they will have the opportunity to make a contribution to Industrial Engineering education.

Payment for Participation:

You will not receive any payment for participating in this research study.

Confidentiality

No personal information will be collected, and survey responses will be collated anonymously using an identifying number known only to the participant and lead investigator. You will need to be contacted by the PI via your email address during the study if you do not respond during the requested time frame between each Delphi round. All data collected will remain confidential. There will be privacy in gathering, storing and handling data. The data will be kept by the PI for six months. After that, all materials will be destroyed. All responses received in the study will be strictly confidential, and your identity will not be divulged. Direct quotes to free-text answers may be used as part of the study report or later Delphi iterations, but these will be not be traceable back to you.

Research ethics

The proposed Delphi study abides by the ethical requirements of the University of the Witwatersrand. A copy of the University of the Witwatersrand ethics committee application and decision letter is available on request. All participants will be asked to complete a consent form.

What do I do now?

Thank you for reading this information sheet and for considering taking part in this research. Please let us know whether or not you would like to take part by replying to this email. If you wish to participate, we would be very grateful if you could also complete the attached consent form. If you have any questions or concerns, please do not hesitate to contact me

Principal Investigator: Khanyiso Vuyelwa 2069190@students.wits.ac.za

Research Supervisor: Prof Raj Siriram raj@alpha-concepts.com

DELPHI STUDY CONSENT FORM

Title of Project: ***Using Market Preference Analytics to maximise Plant Utilisation leading to Flexible Manufacturing System Design and Operations in the FMCG Industry.***

Name of Researcher: Khanyiso Vuyelwa

Please initial box:

1. I confirm that I have read the information sheet for the above study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily.	
2. I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason and without there being any negative consequences or my legal rights being affected. I understand that should I decide to withdraw then information already collected will be included in the data analysis in the study.	
3. I understand that relevant sections of my data collected in the study may be looked at by authorised individuals from the University of Lincoln, the research team and regulatory authorities as part of the research audit process. I give permission for these individuals to have access to these records.	
4. I understand that my name will not be identified during the Delphi survey or in the reports resulting from the research and my personal details will be kept strictly confidential.	
5. I agree that non identifiable quotations and data may be used in this study and may be published in the research thesis, articles, on the study website and presented at conferences.	
6. I agree to take part in the above study.	

Name of Participant: ___________________________ Signature: _______________________Date: ___________________

Name of Researcher: ___________________________ Signature: _______________________Date: ___________________

Please return scanned or electronically completed forms via email to: 2069190@students.wits.ac.za

Please do not hesitate to contact the lead researcher if you have any concerns or questions.

Email: 2069190@students.wits.ac.za

APPENDIX C SAMPLE RESEARCH INSTRUMENT

Using Market Preference Analytics to maximise Plant Utilisation leading to Flexible Manufacturing System Design and Operations in the FMCG Industry

Delphi Study Round 2

For this round you are requested to consider the responses from the previous round, along with key comments by your fellow panelists . Then decide whether their opinions, this applies to Section 3 (Part 2), change your disposition from the previous round or not. Kindly be advised, for the rest of the questions you only have their ratings to consider to influence your rating.

To aid in making the process smooth, the frequency distribution of responses from the previous round for each question are presented. This together with statistical indices viz. the mode, median, 1st quartile (Q1), 3rd quartile (Q3) and the interval quartile range(IQR), for each question in all sections. And lastly, your previous rating is given.

Once you have considered all the presented information you may then proceed to rank/rate each question using the same scales as before; with the information from the other participants in view. Unlike the first round, opinions are optional in this round.

* Required

1. Email address *

Participant Detail

2. Name & Surname *

PART TWO

REMEMBER: Once you have considered all the presented information you may then proceed to rank/rate each question using the same scales as before, with the information from the other participants in view. Unlike the first round, opinions are optional in this round. Please feel free to comment.

Q1 - 1st Quartile
Q3 - 3rd Quartile
IQR - Interval Quartile Range

For Likert Scales:

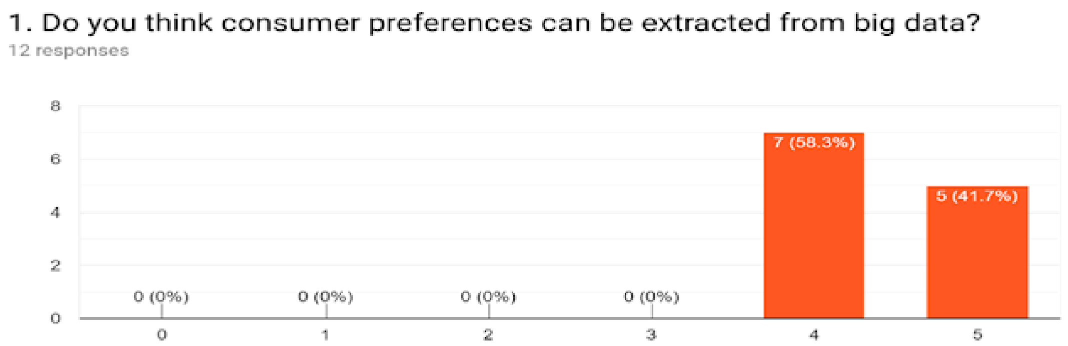
Rank each question using the following the scale:

NOTE:

0- Do Not Know 1-Slightly Possible 5-Significantly Possible

Please remember that your views are very important to this study and therefore please share your views. There are no RIGHT or Wrong answers.

3. 1. Do you think consumer preferences can be extracted from big data? [Your previous rating: 4] *



Q1	4
Q3	5
IQR	1
Median	4
Mode	4

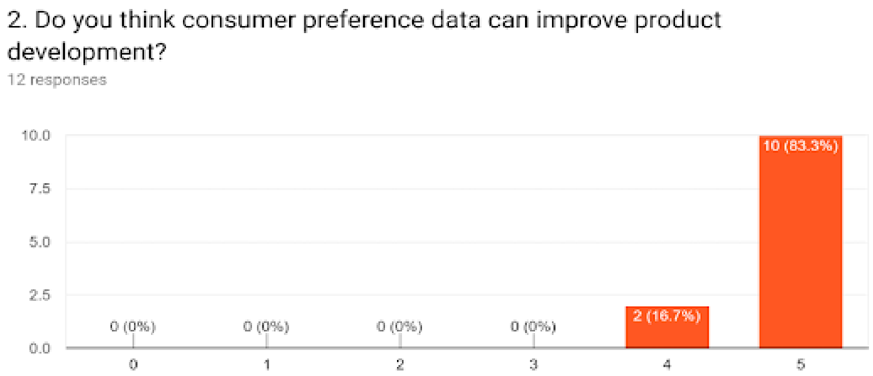
Previous Comments:	Big data has been seen as a complex data base however if it is used correctly it can be a key to learning about customers. Big data can be used to ascertain online consumer habits. Example : Online shopping- Consumers often search for items that they would possibly be interested in. With big data, and predicitive analytics- similar purchase options can be displayed. Age and demographic information can also be trended against product preferences.
	I have been part of a consumer preference study before. Our feedback was directly used to tweak product design or choose the most suitable product from a range. Not sure if this is done with all products.
	Data mining can be used to mine for consumer insights and pattern recognition for various use cases/applications
	It's important to simplify the data to understand the consumer preferences.

Mark only one oval.

0	1	2	3	4	5
⬭	⬭	⬭	⬭	⬭	⬭

4. Please explain

5. 2. Do you think consumer preference data can improve product development? [Your previous rating: 4] *



Q1	5
Q3	5
IQR	0
Median	5
Mode	5

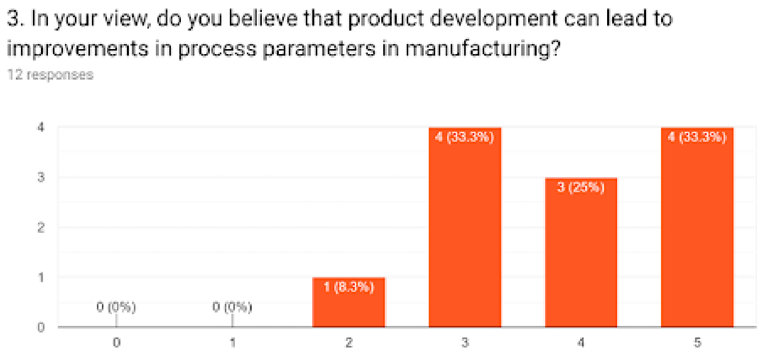
Previous Comments:	Consumer buying pattern behaviour helps give insights as to what consumers find valuable to buy. In turn assisting the manufacturer in developing products for specific segments
	New product development is a core competence in many leading FMCG giants. Organizations who put consumers first will benefit from this. If data is available which highlights consumer preferences- they will be able to narrow their product development options and focus on whats important. They will also be able to sync with the requirements from different LSM [*Living Standards Measure*] groups.
	The consumer has all the power. It is easy to manufacture something. The challenge comes when you have to try and sell your manufactured product. Data could let the manufacturer design products directly to the consumers needs.
	The purpose of manufacturing is to provide to the consumer. Consumer satisfaction can only be improved by product development.

Mark only one oval.

0	1	2	3	4	5
⬭	⬭	⬭	⬭	⬭	⬭

6. Please explain

7. 3. In your view, do you believe that product development can lead to improvements in process parameters in manufacturing? [Your previous rating: 3] *



Q1	3
Q3	5
IQR	2
Median	4
Mode	3

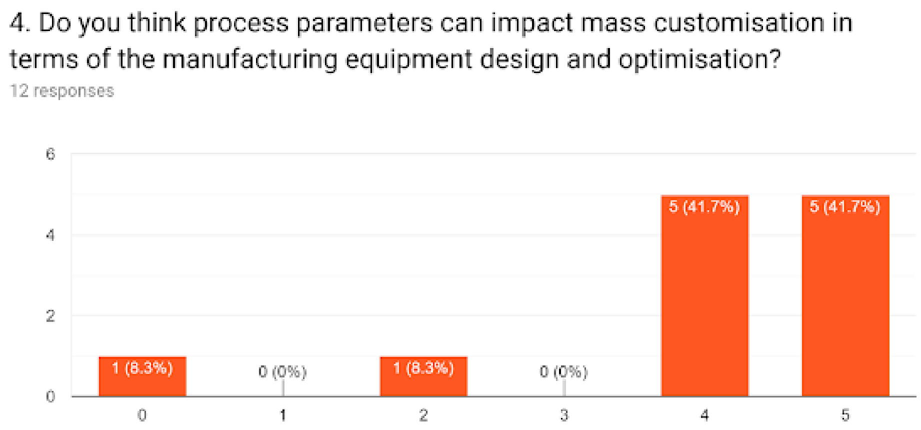
Previous Comments:	The product development process allows for different trial phases eg. Feasibility and Capability trials. When these trials are carried out, process deviations can be reported and means to improve performance can be investigated. Current line capabilities can be tested and the new product development process can allow for flexibility in improvements.
	Developing a product is easy in theory. When it gets down to optimising the process parameter, the issues will come to light only when the product is manufactured for a extended period.
	Not necessarily, as that can only be true when product development and process development are interconnected.
	Yes, by defining and refining ways to produce products, evaluating and implementing advanced manufacturing technologies and bringing new technologies and processes

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

8. Please explain

9. 4. Do you think process parameters can impact mass customisation in terms of the manufacturing equipment design and optimisation? [Your previous rating: 2] *



Q1	4
Q3	5
IQR	1
Median	4
Mode	5

Previous Comments:	Mass customization of manufacturing equipment is difficult to do because consumer preferences change all the time. It's a CAPEX intensive exercise
	Yes, MC can deliver superior performance to manufacturing. MC practices can improve the effectiveness and efficiency of manufacturers' operations, which can be reflected by a set of key performance indicators, such as price, service, delivery, and volume flexibility
	Process parameters are critical and need to be maintained such that product manufacturing can be repeated. Critical parameters need to be established and the impact of the variations in the process on product quality needs to be verified. If volumes increase and product design changes - parameters need

Mark only one oval.

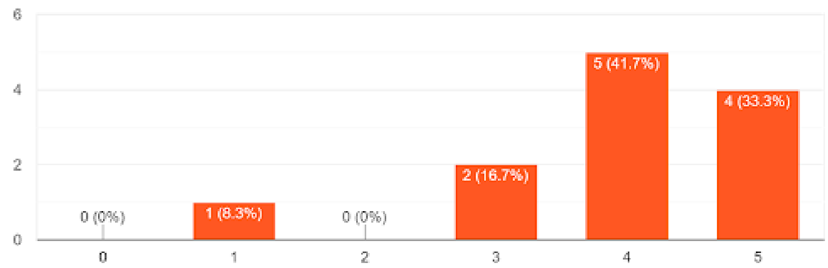
0	1	2	3	4	5
○	○	○	○	○	○

10. Please explain

11. 5. Do you think consumer preferences affect mass customisation in terms of the manufacturing equipment design and optimisation? [Your previous rating: 3] *

5. Do you think consumer preferences affect mass customisation in terms of the manufacturing equipment design and optimisation?

12 responses



Q1	3.75
Q3	5
IQR	1.25
Median	4
Mode	4

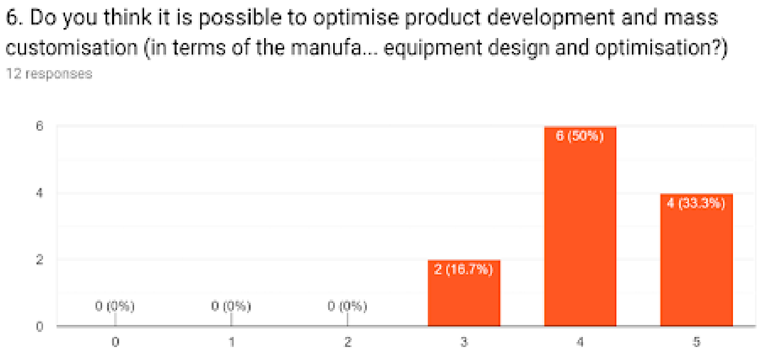
Previous Comments:	The customization in plant is more towards optimization of plant process and outputs.
	There is that congruence in terms of equipment design for mass customization. Keeping abreast with constant change is what manufacturers will be dealing with, this is where 3D printing can make the difference.
	Depending of the type of entity, B2B or B2C, these models of business can also be affected at a process level depending on the nature of the product being manufactured, a change in market demand and time to delivery manufacturing equipment will have to be adapted to respond optimally
	Different LSM groups have different preferences. New product development requires that organizations be flexible in their design. Individuals require variety at different stages. If there is mass customization- there has to be a an option for individual customization which may take a longer time to achieve. Individuals are conscious about pricing , however those who are brand loyal will be willing to try different options on offer.

Mark only one oval.

0 1 2 3 4 5

12. Please explain

13. 6. Do you think it is possible to optimise product development and mass customisation (in terms of the manufacturing equipment design and optimisation?) [Your previous rating: 4]



Q1	4
Q3	5
IQR	1
Median	4
Mode	4

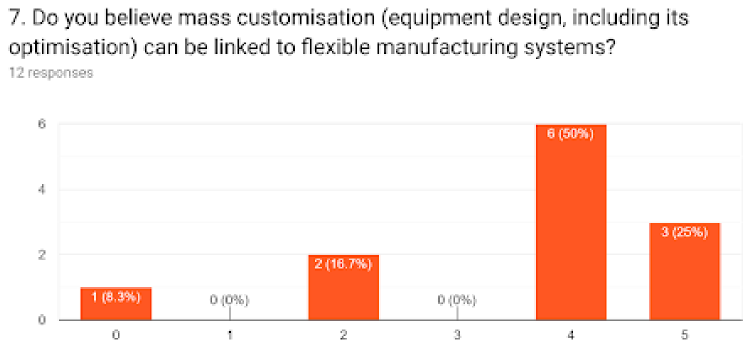
Previous Comments:	Yes- this is possible. Change parts can be designed for equipment which will allow for changes to take place at a later stage. Competitive offerings can be investigated and designs can be built based on designs that are I'm the market. The product formulation base can remain the same but different adaptations can be designed.
	It is being done by many manufacturing companies world wide
	With the yearly data this can be done by reviewing the best selling product and least selling, reviewing the lines which are running in full capacity and the ones with not good output rate.
	Yes, there is a relationship between the two, Mass customization is termed to manufacture customized products with cost flexibility i.e. mass production is enabled at relatively low unit cost. Rapid product development is a collaborative process of engineering to produce a new product into a market

Mark only one oval.

0 1 2 3 4 5

14. Please explain

15. 7. Do you believe mass customisation (equipment design, including its optimisation) can be linked to flexible manufacturing systems? [Your previous rating: 4]



Q1	3.5
Q3	4.25
IQR	0.75
Median	4
Mode	4

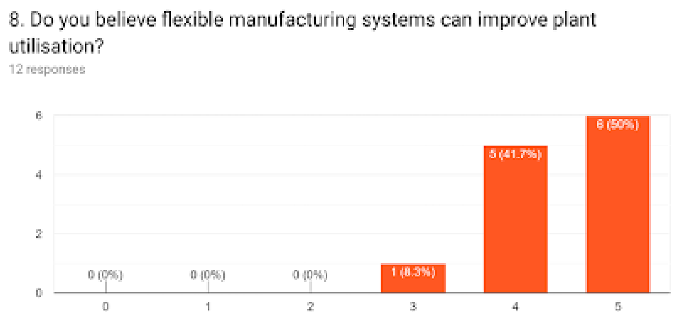
Previous Comments:	Mass customization sometimes do not offer the flexibility as the design is optimized to achieve the greatest output with constant parameters.
	If we have the right people in our manufacturing facilities
	The goal being flexible manufacturing systems, a deliberate migration from one to the other with clearly defined outcomes can make this possible
	Flexibility allows for the equipment to be configured for various market segments. Allowing manufacturers to remain fluid in their service offering

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

16. Please explain

17. 8. Do you believe flexible manufacturing systems can improve plant utilisation? [Your previous rating: 4] *



Q1	4
Q3	5
IQR	1
Median	4.5
Mode	5

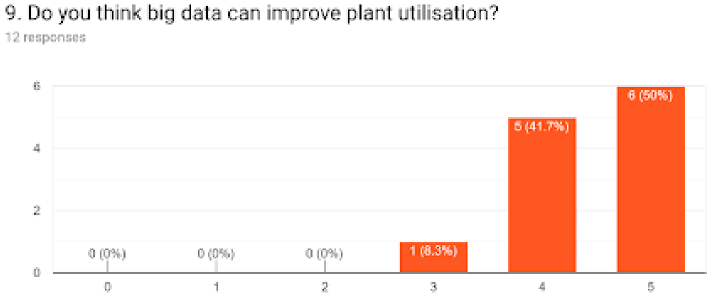
Previous Comments:	Depends on your clients' needs.
	Although changeover times may be higher, focused improvement tools eg. SMED can be used to allow for this flexibility. Being flexible allows for the ability to handle a greater volume eg through internal growth or insourcing
	Due to a need to diversify what manufacturing plants produce, dynamic allocation of sections & sub-sections of the plant need flexible manufacturing systems to keep them viable and diverse in their production capacity
	Yes. Efficient plant utilization can be achieved because these systems allow for proper resource allocation and utility. They also allow for better spatial planning

Mark only one oval.

0 1 2 3 4 5

18. Please explain

19. 9. Do you think big data can improve plant utilisation? [Your previous rating: 4] *



Q1	4
Q3	5
IQR	1
Median	4.5
Mode	5

Previous Comments:	It doesn't have to be big really, just sufficient enough
	Big data can be used in different forms to improve plant utilisation eg. Preventative maintenance- where equipment conditions are monitored and fixed before failure. Real time data can be analyzed and trends be tracked. Machine performance can be monitored and the impact on product quality can be assessed.
	based on data available the management can plan which products to produce and which can be delisted, this will intern enhance the utilization
	It all depends on how it processed - I know big data improves the efficiencies of the plant and this results into less waste

Mark only one oval.

0	1	2	3	4	5
⬭	⬭	⬭	⬭	⬭	⬭

20. Please explain

____

____

____

____

____

PART THREE

For each of the following issues, evaluate their importance in terms of using analytics to maximise Plant Utilisation through Flexible Manufacturing Design and Operations in the FMCG Industry.

Kindly note each issue MUST be rated as it impacts the present (Importance NOW) and the future (Importance 5 years from now).

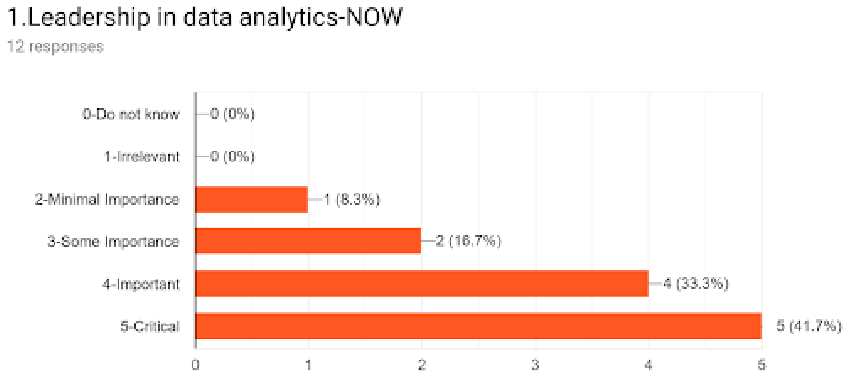
The weighting for each is as follows:

0-Do Not Know   1-Irrelevant   2-Minimal Importance   3-Some Importance   4-Important   5-Critical

21. 1.Leadership in data analytics-NOW [Your previous rating: 5] *

Kindly the issue's Importance NOW

Q1	3.75
Q3	5
IQR	1.25
Median	4
Mode	5



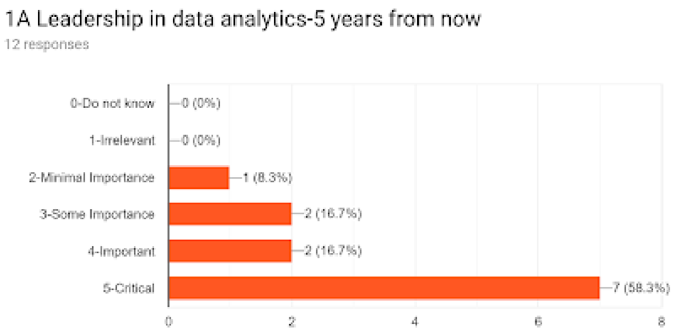
Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

22. 1A Leadership in data analytics-5 years from now [Your previous rating: 3] *

Kindly the issue's Importance 5 years from now

Q1	3.75
Q3	5
IQR	1.25
Median	5
Mode	5



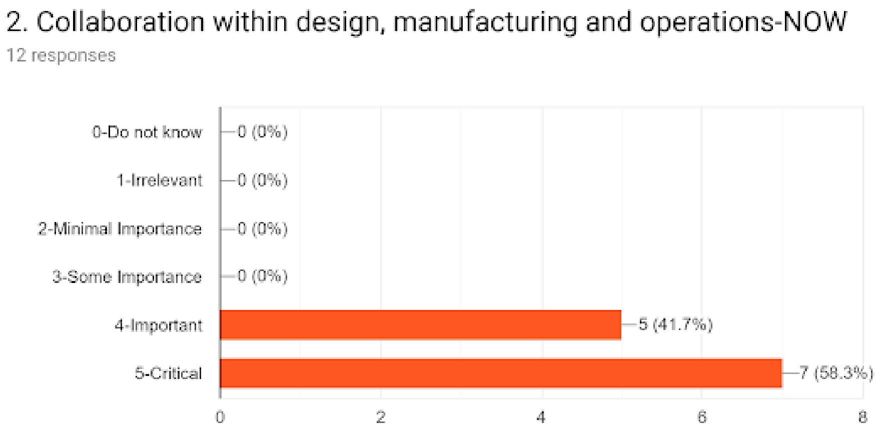
Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

23. 2. Collaboration within design, manufacturing and operations-NOW [Your previous rating: 4] *

Kindly the issue's Importance now

Q1	4
Q3	5
IQR	1
Median	5
Mode	5



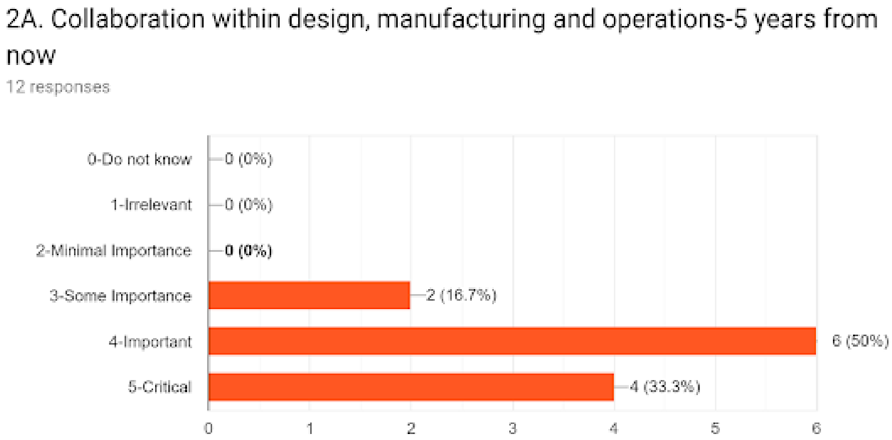
Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

24. 2A. Collaboration within design, manufacturing and operations-5 years from now [Your previous rating: 4] *

Kindly the issue's Importance 5 years from now

Q1	4
Q3	5
IQR	1
Median	4
Mode	4



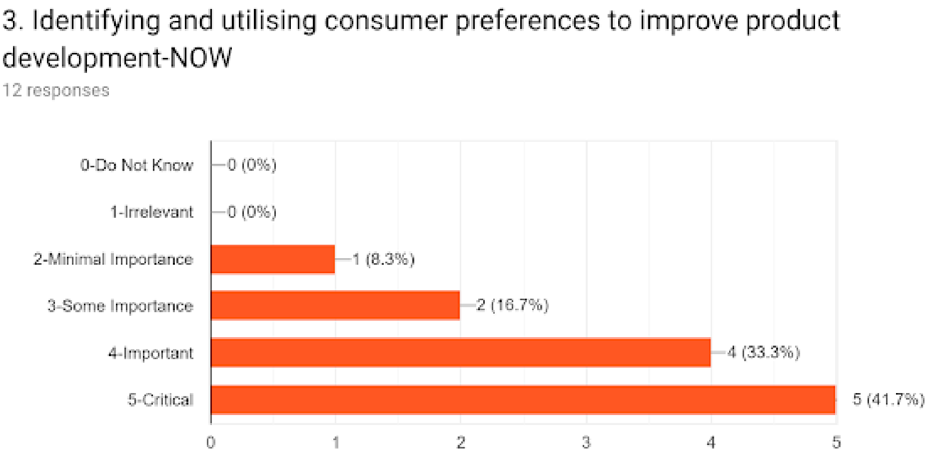
Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

25. 3. Identifying and utilising consumer preferences to improve product development-NOW [Your previous rating: 4] *

Kindly rate the issue's Importance now

Q1	3.75
Q3	5
IQR	1.25
Median	4
Mode	5



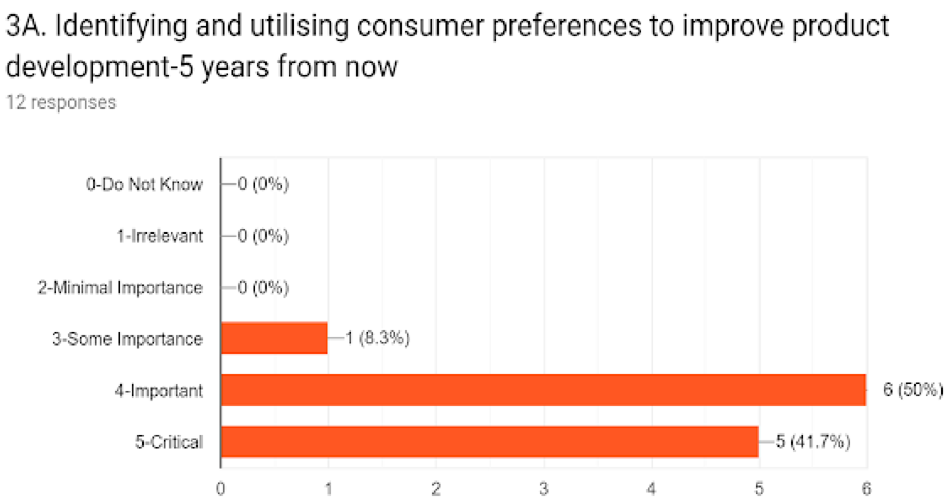
Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

26. 3A. Identifying and utilising consumer preferences to improve product development-5 years from now [Your previous rating: 4] *

Kindly rate the issue's Importance 5 years from now

Q1	4
Q3	5
IQR	1
Median	4
Mode	4



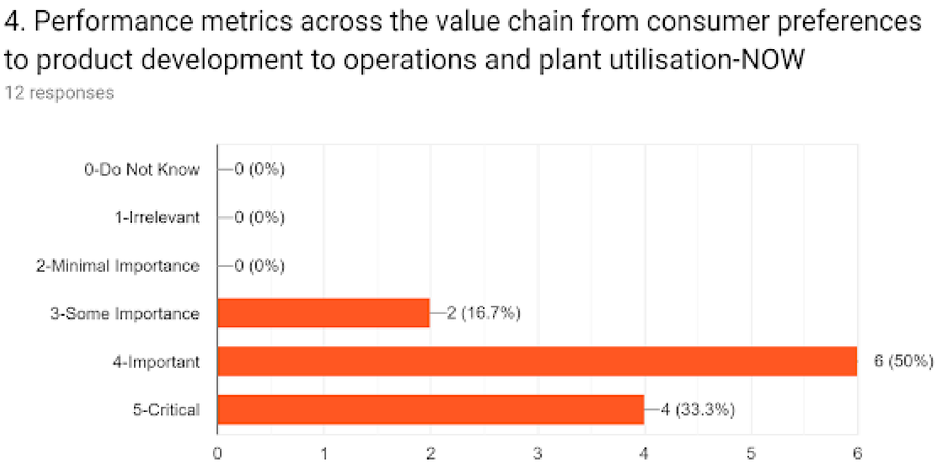
Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

27. 4. Performance metrics across the value chain from consumer preferences to product development to operations and plant utilisation-NOW [Your previous rating: 4] *

Kindly rate the issue's Importance now

Q1	4
Q3	5
IQR	1
Median	4
Mode	4



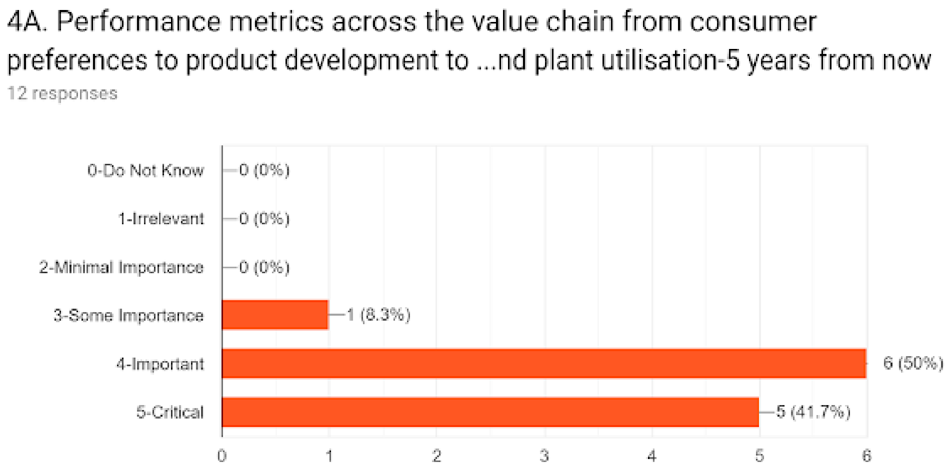
Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

28. 4A. Performance metrics across the value chain from consumer preferences to product development to operations and plant utilisation-5 years from NOW [Your previous rating: 4] *

Kindly rate the issue's Importance 5 years from now

Q1	4
Q3	5
IQR	1
Median	4
Mode	4



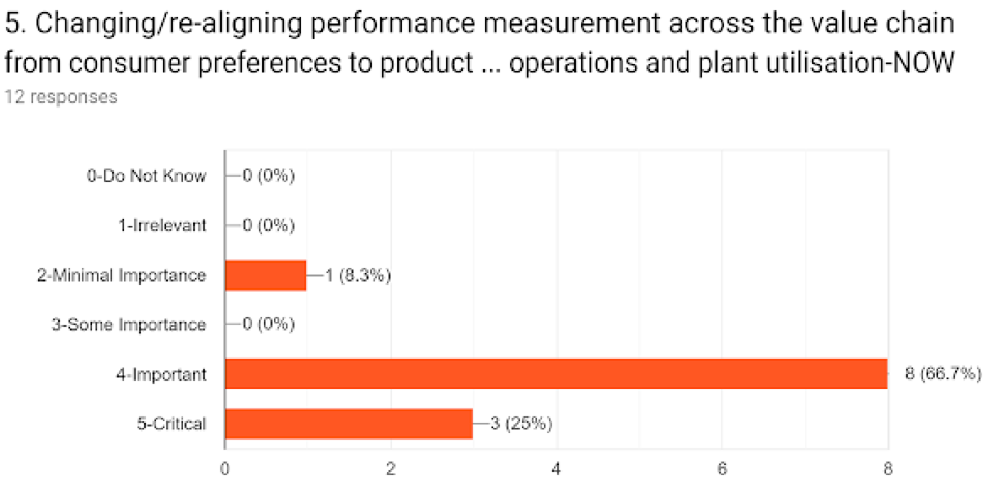
Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

29. 5. Changing/re-aligning performance measurement across the value chain from consumer preferences to product development to operations and plant utilisation-NOW [Your previous rating: 4] *

Kindly rate the issue's Importance now

Q1	4
Q3	4.25
IQR	0.25
Median	4
Mode	4



Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

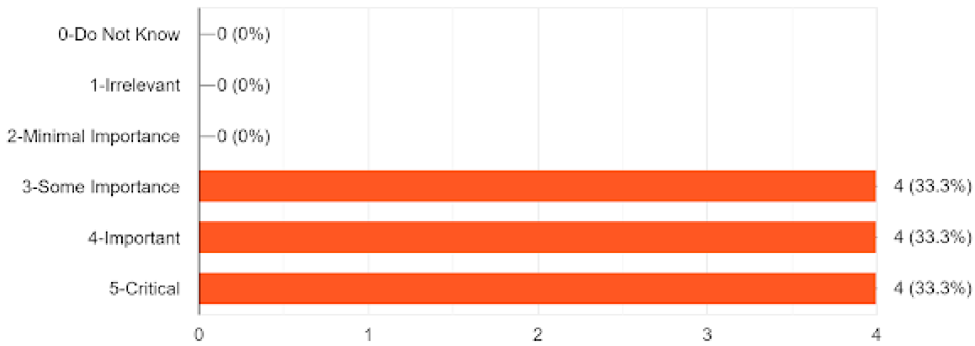
30. 5A. Changing/re-aligning performance measurement across the value chain from consumer preferences to product development to operations and plant utilisation-5 years from now [Your previous rating: 3] *

Kindly rate the issue's Importance 5 years from now

5A. Changing/re-aligning performance measurement across the value chain from consumer preferences to product ...nd plant utilisation-5 years from now

12 responses

Q1	3
Q3	5
IQR	2
Median	4
Mode	4



Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

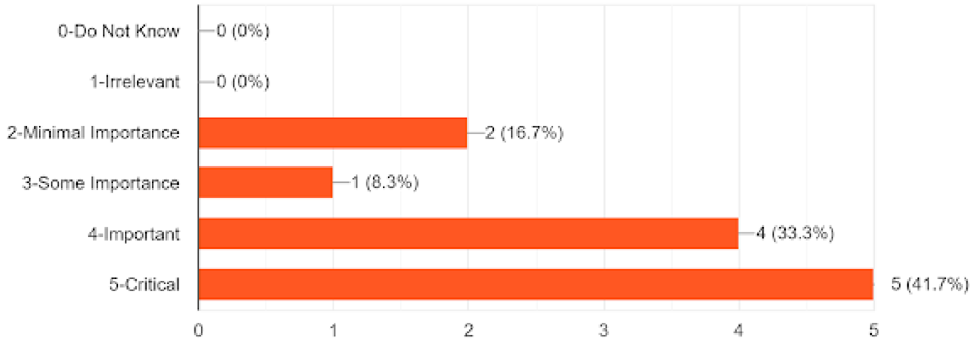
31. 6. Managing product development by drawing on the capabilities of big data-NOW [Your previous rating: 4] *

Kindly rate the issue's now

6. Managing product development by drawing on the capabilities of big data-NOW

12 responses

Q1	3.75
Q3	5
IQR	1.25
Median	4
Mode	5



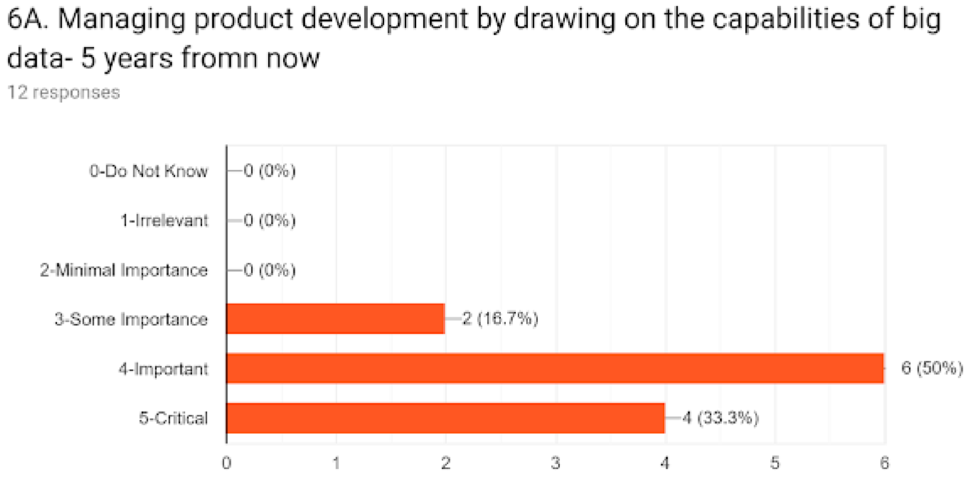
Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

32. 6A. Managing product development by drawing on the capabilities of big data- 5 years fromn now [Your previous rating: 4] *

Kindly rate the issue's Importance 5 years from now

Q1	4
Q3	5
IQR	1
Median	4
Mode	4



Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

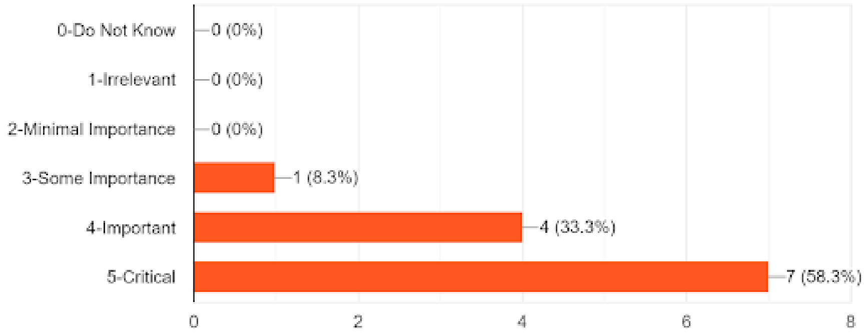
33. 7. Managing visibility and control of the value chain through the use of big data-NOW [Your previous rating: 4] *

Kindly rate the issue's Importance Now

7. Managing visibility and control of the value chain through the use of big data-NOW

12 responses

Q1	4
Q3	5
IQR	1
Median	5
Mode	5



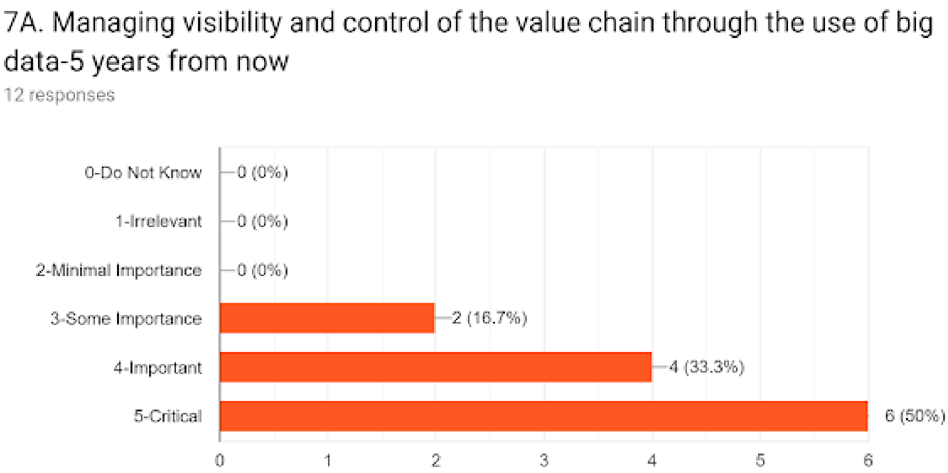
Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

34. 7A. Managing visibility and control of the value chain through the use of big data-5 years from now [Your previous rating: 4] *

Kindly rate the issue's Importance 5 years from now

Q1	4
Q3	5
IQR	1
Median	4.5
Mode	5



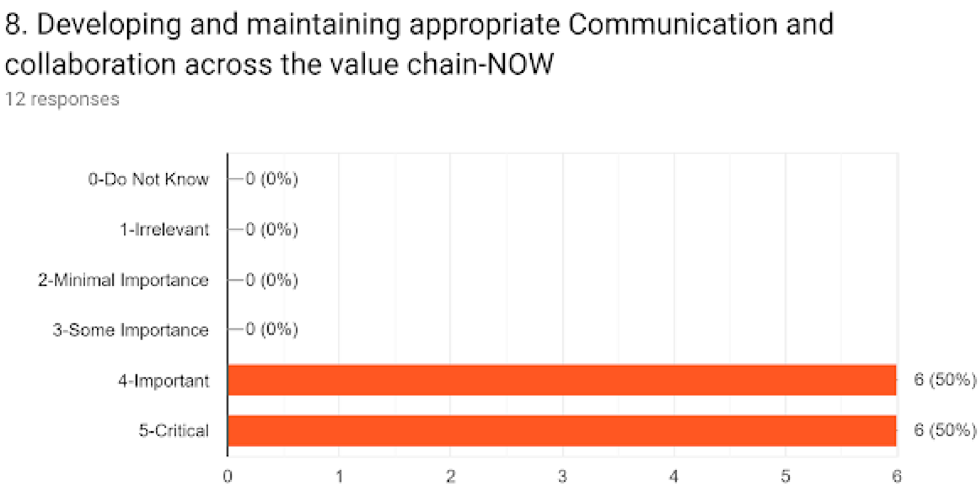
Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

35. 8. Developing and maintaining appropriate Communication and collaboration across the value chain-NOW [Your previous rating: 4] *

Kindly rate the issue's Importance Now

Q1	4
Q3	5
IQR	1
Median	4.5
Mode	5



Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

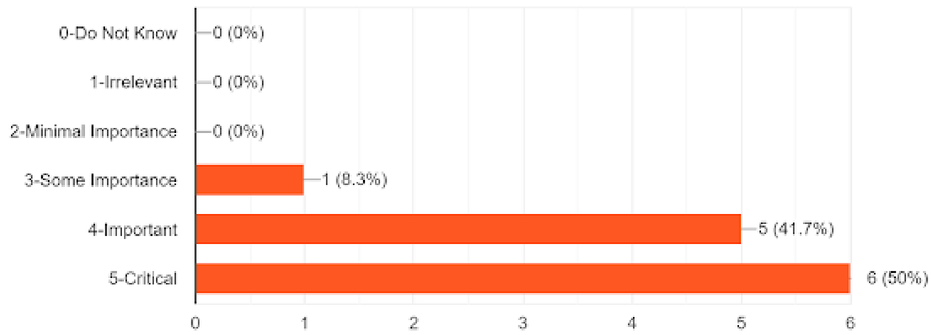
36. 8A. Developing and maintaining appropriate Communication and collaboration across the value chain-5 years from now [Your previous rating: 4] *

Kindly rate the issue's Importance 5 years from now

Q1	4
Q3	5
IQR	1
Median	4.5
Mode	5

8A. Developing and maintaining appropriate Communication and collaboration across the value chain-5 years from now

12 responses



Check all that apply.

- [ ] 0-Do Not Know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

PART FOUR

The following Section contains issues raised by the panelists.

For each of the following issues, evaluate their importance in terms of using analytics to maximise Plant Utilisation through Flexible Manufacturing Design and Operations in the FMCG Industry.

Kindly note each issue MUST be rated as it impacts the present (Importance NOW) and the future (Importance 5 years from now).

The weighting for each is as follows:

0-Do Not Know 1-Irrelevant 2-Minimal Importance 3-Some Importance 4-Important 5-Critical

37. 1. Launching new products in different segments, Like First taste preferable to kids can be decided based on the data available. *

Kindly the issue's Importance at present.

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

38. 1A. Launching new products in different segments, Like First taste preferable to kids can be decided based on the data available. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

39. 2. Demand planning of developed products *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

40. 2A. Demand planning of developed products. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

41. 3. Understanding the cycle of production throughout the value chain better *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

42. 3A. Understanding the cycle of production throughout the value chain better. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

43. 4. Strategic decision making capability improvements *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

44. 4A. Strategic decision making capability improvements. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

45. 5. Change in talent requirements and capability *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

46. 5A. Change in talent requirements and capability. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

47. 6. Seven day data, process and information cycle appraisal/reporting optimisation *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

48. 6A. Seven day data, process and information cycle appraisal/reporting optimisation. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

49. 7. Running field team surveys on daily issues faced by front line staff/teams, thus gathering insights on what and how to improve on an on-going basis *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

50. 7A. Running field team surveys on daily issues faced by front line staff/teams, thus gathering insights on what and how to improve on an on-going basis. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

51. 8. Degree to which big data can improve operational efficiency and can improve customer service. *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

52. 8A. Degree to which big data can improve operational efficiency and can improve customer service. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

53. 9. How quickly the big data can be utilized to deliver results. NOW *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

54. 9A. How quickly the big data can be utilized to deliver results. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

55. 10. Understanding the [organisation's] vision in five years. NOW *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

56. 10A. Understanding the [organisation's] vision in five years.5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

57. 11. The Important factors which need to be considered when big data is used for monitoring. NOW *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

58. 11A. The Important factors which need to be considered when big data is used for monitoring. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

59. 12. Consumer privacy. NOW *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

60. 12A. Consumer privacy. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

61. 13. Ethics. NOW *

Kindly the issue's Importance at present.

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

62. 13A. Ethics. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

63. 14. Predictive additional capability. NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

64. 14A. Predictive additional capability. 5 years from NOW *

Kindly the issue's Importance at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

65. 15. The use of automation and artificial intelligence. NOW *

Kindly the issue's Importance 5 years at present

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical

66. 15A. The use of automation and artificial intelligence. 5 years from NOW *

Kindly the issue's Importance 5 years from now

Check all that apply.

- [ ] 0-Do not know
- [ ] 1-Irrelevant
- [ ] 2-Minimal Importance
- [ ] 3-Some Importance
- [ ] 4-Important
- [ ] 5-Critical