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Exploring the mindsets and behaviours necessary for cultivating data-driven decision making within an organisation

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WITS Business School

Thesis presented in partial fulfilment for the degree of Master of Business Administration to the Faculty of Commerce, Law, and Management, University of the Witwatersrand

(Research Article)

Johannesburg, March 2021

DECLARATION

I Jef Andreas Jacobs declare that this research report entitled 'Exploring the mindsets and behaviours necessary for cultivating data-driven decision making within an organisation ' is my own unaided work. I have acknowledged, attributed, and referenced all ideas sourced elsewhere. I am hereby submitting it in partial fulfilment of the requirements of the degree of Master of Business Administration at the University of the Witwatersrand, Johannesburg. I have not submitted this report before for any other degree or examination to any other institution.



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Signed at Johannesburg on 21st March 2021

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ABSTRACT

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Thesis title: **Exploring the mindsets and behaviours necessary for cultivating data-driven decision making within an organisation**

The advancement of data storage and processing technologies and the exponential growth in data generated by online activity and smart devices has stimulated a desire by organisations to be more data-driven in their decision making. Adopting a data-driven approach to decision making is associated with improved organisation performance and innovation. However, most organisations are struggling to realise these benefits because crafting clear data use strategies and cultivating a culture of data-driven decision making appears to be more challenging than investing in relevant technologies or implementing organisational processes. Given this situation, the purpose of this study is to investigate the mindsets and associated behaviours of leaders and their teams who are successfully leveraging data to improve market competitiveness or impact. Using a qualitative research strategy and semi-structured interview processes with six experienced professionals, this research paper identifies six mindsets and associated behaviours that senior decision makers should adopt to help overcome the common *people* related challenges that hinder effective data-driven decision making in organisations. Prime examples include senior leaders as data advocates who communicate and reflect of data-driven decisions and leaders who encourage quick experimentation with an openness to failure. Based on these findings the study recommends that senior decision makers, working in organisations that have invested in data related technologies and skills, acknowledge that their attitudes and behaviours have a direct impact on how successful any data strategy and investment will be. These influential leaders or managers need to understand and believe in the data-driven decision making process and they need to ensure the implementation of key activities that ensure informed actions are eventually taken on the back of data collected. Research in this field mostly predominantly discusses issues related to numerical techniques, technological innovations and studies around impact. This study contributes to the current body of knowledge by investigating leadership and managerial aspects of data use or Big Data in organisational decision making.

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DEFINITION OF KEY TERMS AND CONCEPTS

Mindset: A person's way of thinking, their opinions, mentality, outlook and points of view. Cambridge Business English Dictionary © Cambridge University Press and Cambridge Advanced Learner's Dictionary & Thesaurus © Cambridge University Press.

Decision makers: Individuals within an organisation that are responsible for making decisions that may impact organisational performance, strategy or structure such as senior managers, all executives, team leaders, managing directors etc.

Big Data: Akter, Wamba, Gunasekaran, and others (2016) define the term *Big Data* as a general term for how data, that is defined by relatively large volumes, variety, velocity, veracity and value, is managed, processed and analysed for data-driven decision making for "sustained value delivery, measuring performance and establishing competitive advantages".

1 INTRODUCTION TO THE RESEARCH

1.1 Background and context

More generally, this research investigates the mindsets and behaviours necessary for cultivating and leading data-driven organisations. However, before getting to the research conceptualisation (Section 1.2), we briefly introduce the terms and concepts that we have used in conceptualising this research in Section 1.1 generally and broadly—while Chapter 2 has a more specific and detailed discussion on the research context. The research conceptualisation section provides for the research problem statement (Section 1.2.1) and consequently the purpose of this research (Section 1.2.2) as well as the research questions (Section 1.2.3). The delimitations and assumptions of the research study are in Section 1.3 while we discuss the significance of the research study in Section 1.4 and provide a preface to the research report in Section 1.5.

1.1.1 Strategic decision making

Making strategic decisions is a fundamental component of management within any organisation and a key responsibility of decision makers (Crainer, 2007). Jansen, Curseu, Vermeulen, and others (2011) define strategic decision making as the act of allocating limited resources and people towards specific organisational objectives. The authors also highlight that it does not matter whether a decision was based on intuition or careful conscious consideration, so long as it is deemed an effective decision. An effective decision can be defined as a decision that ultimately achieves the desired objectives of the decision maker at the time of making the decision (Jansen, Curseu, Vermeulen, et al., 2011). For example, an organisation may decide to expand operations into a new market to increase overall profits. The effectiveness of that decision, or whether the decision was a *good decision* or a *bad decision*, will be judged according to how well overall profit levels increased as a result of entering that market. Each decision a manger makes is a risk that he or she is taking since the ultimate outcome, or effectiveness, of that decision is not known at the time of making that decision (Crainer, 2007). Therefore, reducing the risk or uncertainty of a decision, especially those with large opportunity costs, is key for achieving organisational objectives including, but not limited to, financial performance and long-term sustainability. Salas, Rosen, and DiazGranados (2010) contend that

reducing decision making uncertainty or risk can be achieved through a combination of explicit conscious reasoning and expertise based intuition.

1.1.2 Advancements in information technology and data

Three megatrends are altering strategic decision making. The first is the rapid increase in the performance, affordability and accessibility of information technology (IT) making it possible for more organisations to quickly and accurately process large amounts of information (Alharthi, Krotov, & Bowman, 2017; Barton & Court, 2012). The second trend relates to continuous improvements in data storage technologies and the capabilities of software applications that allow people to take advantage of these improving technologies (Niebel, Rasel, & Viete, 2019). The third and last megatrend relates to the large volume of data that is constantly being collected from connected devices (i.e., the widespread application of sensors or otherwise known as the internet of things (IoT)) and online user-generated content (Barton & Court, 2012; Niebel, Rasel, & Viete, 2019). The outlook is that the "big data" megatrend, of collecting and using data is likely to continue increasing at an exponential rate (UNCTAD, 2018).

Overall, the three megatrends mentioned above allow for faster and more accurate decision making, thereby reducing decision making risk and enhancing the overall strategic decision making process (Barton & Court, 2012; Niebel, Rasel, & Viete, 2019). The use of data in decision making is referred to as data-driven decision making.

1.1.3 Data-driven decision making

A data-driven organisation is one that leverages information technology to collect, manage and transform data into relevant insights for strategic decision making, monitoring, evaluation and communication purposes (Brynjolfsson & McElheran, 2016a). These firms transform data (that they trust or consider as factual) into insights, and then into decisions, and then successfully execute on those decisions (Tabesh, Mousavidin, & Hasani, 2019). Within data-driven organisations the decision-making and strategy-setting process will continue to rely less on once-off data collection projects as more and different information becomes almost immediately available to leaders and decision makers (Niebel, Rasel, & Viete, 2019; Tambe, 2014). Data-driven organisations benefit from insights, derived from data analysis processes, to influence decisions across

multiple components of their organisations, such as marketing and sales, product innovation or operations to name a few (McKinsey & Company, 2018).

1.1.4 The benefits of being a data-driven organisation

It is worthwhile noting the benefits of adopting a data-driven strategy and approach to overall decision-making. Niebel, Rasel, and Viete (2019) highlight that new insights gained from data can reduce the time and the costs associated with an organisation's research and development process. In fact, the authors also discuss how that data itself can become or define a new product and that data-driven firms innovate more frequently and more intensely than other firms.

In terms of productivity, Brynjolfsson and McElheran (2016b) found that manufacturing firms which adopt a data-driven approach enjoy a 5-6 per cent higher rate of productivity and market value. Müller, Fay and Brocke (2018) conduct a similar econometric analysis for a wider set of industries and find similar results (3 to 7 per cent increases) depending, however, on the industry and its existing exposure to information systems.

Data use approaches quickly make what was once invisible now visible (Barton & Court, 2012) and this significantly improves the quality and speed of interactions between organisations and their staff, customers, competitors and suppliers (Tambe, 2014). It is for all these reasons and opportunities that an increasing number of organisations are interested in adopting data-driven decision making. It will be demonstrated below, however, that such a transition is not easy and that organisational decision makers play a particularly important role in ensuring investments into data use transformations eventually translate into desired organisational outcomes.

1.2 Research conceptualisation

1.2.1 The research problem statement

Academic interest in data-driven organisations and data use interventions (especially big data strategies) continues to increase (Mishra, Luo, Jiang, et al. 2017; NewVantage Partners, 2020). However, as the interest, hype and investments continue to grow the reality is that many barriers are preventing most organisations from fully realising their

data use objectives and outcomes (Alharthi, Krotov, & Bowman, 2017; Posavec & Krajnović, 2016).

What is generally well documented and understood are (i) the potential benefits of adopting a data-driven approach to strategic decision making, (ii) the specific organisational components that are necessary for an organisation to become data-driven, and (iii) the typical barriers or challenges organisations face when implementing their data use strategies.

It appears, based on academic and industry leading research, that organisations are battling with the *human* related aspects of cultivating and leading data-driven organisations. That is, developing clear data use strategies and the necessary individual and group (culture) attributes critical for effective organisation wide data-driven decision making. This is not surprising given the rapid advancements in information technology and increasing amounts of data being generated, as mentioned in Section 1.1.2 above. Overall, it appears that researchers and organisations know where the challenges lie and what the key binding constraints are, however, they do not necessarily know how to address all of them, specifically the *human* related barriers.

The importance of decision makers in motivating staff, guiding activities (strategy), developing staff capabilities and cultivating desired organisational cultures is well understood and accepted. It is, therefore, clear that leaders play a critical part in developing the necessary cultures and leading the implementation of data use strategies. But many leaders today did not study or accumulate their expertise in a data-driven context (due to the rapid and recent advances in IT and data), yet they are now tasked with role modelling the right behaviours and making key investment decisions in technologies they do not fully understand, or with making decisions that are based on data insights that go against their existing beliefs.

This paper will illustrate the important role of senior decisions makers with respect to overcoming the common data use and data culture barriers organisations are facing by investigating the ideal behaviours and mindsets that drive those behaviours of data-driven decision makers. More critically, the paper argues that leaders aiming to cultivate or lead data-driven organisations must possess the right mindsets or else desired objectives or outcomes will not be achieved in time or at all.

1.2.2 The research purpose (objectives) statement

This paper aims to achieve two main outcomes. The first is to provide leaders and other senior decision makers of organisations an understanding of the mindsets and associated behaviours they need to possess (or develop) and practise in order to cultivate a data-driven decision making culture within their organisations and to realise the benefits of their broader data use strategies. This will hopefully help leaders and other practitioners overcome the common "data to impact" barriers many organisations are facing and lead to better designed, and therefore more effective, data use interventions and data culture transformation projects. Secondly, the paper aims to bring data-use and big data research closer to the heart of business leadership and management, since most literature on data-driven decision making predominantly focuses on the technical conceptual components such as technical data management technologies and data analytics skills.

1.2.3 The research questions as well as where applicable accompanying research propositions

This paper argues that the solution to many of the *human* related barriers that organisations are currently facing, with regards to implementing data-driven decision making, lies within the attributes and behaviours of key decision makers within these organisations, and that these mindsets and behaviours can be identified by interviewing individuals who have direct experience in working with successful data-driven decision makers or working within data-driven organisations.

This paper therefore aims to answer the following two key questions:

- what mindsets differentiate data-driven decision makers from non-data-driven decision makers, and
- what are the behaviours associated to these mindsets that lead to effective data-driven cultures and data-driven decision making?

1.3 Delimitations and assumptions of the research study

The following boundaries define and limit the scope of this research study:

- This paper will not focus on technical skills such as data analytics, data engineering, statistical techniques, software skills, etc. required of data or systems architects, business analysts, IT practitioners or other technical managers.
- This paper does not focus on a single type or size of organisation or industry.
- This paper does not focus on a single geography.
- This paper does not investigate broader leadership knowledge or mindsets.
- This paper does not aim to empirically prove which identified mindsets are more or less important or the magnitude of impact of those mindsets identified.

1.4 Significance of the research study

"Advances in information and communication technologies led to big data technologies which enable information visibility in organisations and give leaders powerful means for empowering and leading employees to make value on the basis of data from environment [*sic*]" (Lukic, 2015, p. 293). Yet research on the leadership mindsets and behaviours necessary to achieve this goal remains sparse and inconclusive. "Despite its acknowledged role as a potential source of value for all businesses, big data remains a fashionable but not well understood or fully clarified concept" (Pugna, Dutescu, & Stănilă, 2019, p. 1). Confirming these knowledge gaps, Scholz (2017) posits that Big Data are not researched from a human perspective, which precludes the human factor in most of the investigations undertaken.

The consequences of not addressing the questions raised in this research project are (i) continued disappointment by investors and leadership teams with respect to the outcomes (or rate of progress) of their data use interventions and, therefore investments, (ii) continued uncertainty with respect to what organisational leaders or senior decision makers need to do and who they need to be to unlock desired outcomes, and (iii) sub-optimal data use intervention designs by data use practitioners or service providers, due to insufficient attention given to the specific mindsets and behaviours needed of leaders and senior decision makers in order to realise desired objectives. In filling these knowledge gaps, the present study will (i) assist organisational decision makers in making more

informed and effective data-driven decisions and (ii) assist in identifying and addressing organisational bottlenecks (especially *people* related barriers) hindering the realisation of their Big Data or data use strategies.

1.5 Preface to the research report

To this end, the report has six chapters. Following this introductory chapter, Chapter 2 provides a literature review covering the problem, the past studies, the explanatory framework and the conceptual framework. Chapter 3 discusses the research strategy, design, procedures, reliability and validity measures as well as limitations. Chapter 4 and Chapter 5 presents and discusses the findings, respectively, to interrogating our research questions while Chapter 6 summarises and concludes the research.

1.6 Conclusion

Chapter one conceptualised the study, which examines the leadership mindsets and behaviours necessary to promote and sustain use of data in organisational decision making. Using a qualitative analytical framework, the study aims to provide a unique perspective and understanding of the leadership and management attributes that unlock the full application and impact of data. Chapter two is presented next with literature review.

2 LITERATURE REVIEW

Introduction

This chapter has three broad objectives; namely to understand the research problem, to identify the knowledge gap, and to develop a framework for interpreting the research findings. Specifically, in Section 2.1, we detail the research problem. In Section 2.2, we review literature on studies that have attempted a similar study or research. With information arising from Section 2.2, we identify and detail qualitative attributes that are key to this research in Section 2.3 as well as a framework that we will use to interpret our research findings in Section 2.4.

2.1 Poor data-use cultures and unclear data-use strategies

There is a plethora of literature available regarding *what* organisations need, and need to do, to transform into data-driven organisations, especially with regards to data use interventions such as Big Data strategies (Cecilia Adrian, 2017; McAfee & Brynjolfsson, 2012; Mikalef, Pappas, Krogstie, & Giannakos, 2018. However, current academic and non-academic literature reveals that a significant percentage of organisations that are pursuing data use strategies are reporting unsatisfactory progress or outcomes with regards to the pace and magnitude of benefits realised (ATKearney, 2019; McKinsey & Company, 2018; NewVantage Partners, 2020; Rizzuto & Reeves, 2007; Tabesh, Mousavidin, & Hasani, 2019).

Academic and industry research investigating the reasons why organisations are not progressing fast enough in terms of their data use objectives indicate that *people* or *human* related factors, such as skills, culture or strategy development are mostly to blame (Rizzuto & Reeves, 2007). In a 2019 survey of senior executive decision makers from 72 different organisations, 91 per cent of respondents indicated that their main challenge to becoming a data-driven organisation was related to human factors while the remaining 9 per cent indicated technological factors (NewVantage Partners, 2020). This research correlates well with other Big Data industry surveys. In 2019, ATKearney in partnership with the Melbourne Business School, surveyed decision makers from over 350 organisations across 46 countries to understand the business benefits of adopting analytics (ATKearney,

2019). The authors found that only a small portion (6 per cent) of the organisations they surveyed were enjoying significant returns on their investments and that what differentiates these "leaders" from the other 94 per cent of organisations surveyed is (i) a clearly defined strategy for using data, (ii) senior level encouragement and support for analytical experimentation, (iii) an optimal mix of analytics understanding across the entire organisation, and (iv) an organisation-wide data-driven decision making culture. A 2019 survey (GoDataDriven, 2019) of 710 professionals from within the data and artificial intelligence (AI) industry asked respondents to rank aspects of data strategies from most to least important. Out of the eight categories, the top three were *people* related aspects highlighting the importance of (i) a clear data strategy and vision, (ii) support from management, and (iii) available talent, while "Supporting Systems" and "Processes" came in fourth and sixth place, respectively. The insights from these industry reports and surveys highlight two important trends. The first is that, when it comes to data use interventions, organisations are reporting relatively less *technology* or *process* related challenges compared to *people* related challenges (Alharthi, Krotov, & Bowman, 2017; McAfee & Brynjolfsson, 2012; Mikalef, Pappas, Krogstie, & Giannakos, 2018). The second, is that addressing the *people* related factors seems to be far more important (or impactful) than the other components of data use interventions or frameworks. This is not surprising given that decision making, whether data-driven or not, is fundamentally a human process (Crainer, 2007; Posavec & Krajnović, 2016).

Research also points to the fact that there is confusion and different interpretations of common *data use* terms across and within different research and industry domains (Coburn & Turner, 2011; Mandinach & Gummer, 2016; Mikalef, Pappas, Krogstie, & Giannakos, 2018). If different interpretations of concepts like *data literacy*, *data insights, Big Data analytics*, *data use culture*, etc. exist among team members, managers and executive decision makers, then it is likely that different perspectives and opinions on what success looks like (vision and objectives) and what actions are needed to get there (strategies) exist too. Indeed, current literature suggests that a clearly defined and articulated data use strategy and roadmap are key to ensuring organisation-wide buy in and the cultivation of an effective data-driven culture (Alharthi, Krotov, & Bowman, 2017; McAfee & Brynjolfsson, 2012; Posavec & Krajnović, 2016; Rizzuto & Reeves, 2007; Tabesh, Mousavidin, & Hasani, 2019; The Economist Intelligence Unit, 2013).

While it is clear that individuals in senior leadership positions are responsible for articulating organisation data use objectives and strategies (McKinsey & Company, 2018; The Economist Intelligence Unit, 2013), it appears that there is still a lack of understanding of what is needed in terms of mindsets and behaviours from these senior decision makers (Tabesh, Mousavidin, & Hasani, 2019; The Economist Intelligence Unit, 2013).

So, even with clear definitions and understandings of different *data use* terms, clarity in terms of each individual's responsibilities towards realising an organisation's data use strategy or how data will be used to realise an organisation's strategy, is still needed to ensure organisation-wide alignment and buy-in. Otherwise issues of misuse, inertia or resistance will arise when stakeholders (especially senior decision makers) disagree on the value, approach or objectives of data use strategies (Alharthi, Krotov, & Bowman, 2017; Posavec & Krajnović, 2016) or when target users of new tools or processes feel ill-equipped or dismiss long-term expectations (Rizzuto & Reeves, 2007).

A deeper review of literature investigating the challenges that organisations (private and public) are facing, with respect to the *people* and *leadership* issues negatively affecting the successful implementation of data use strategies, highlights three common root-causes: (i) an inadequate rate of knowledge accumulation by leaders, practitioners and researchers, (ii) a deficit in the supply of labour with the necessary skills, mindsets and knowledge to implement data use strategies, and (iii) a lack of 21st century skills being taught in basic and tertiary education institutions.

Many authors have argued that more collaboration between different fields of study is required in order to better understand the often complex human challenges related to IT or data use interventions (Coburn & Turner, 2011; Mandinach, 2012; Rizzuto & Reeves, 2007; Sivarajah, Kamal, Irani, & Weerakkody, 2017). Rizzuto and Reeves (2007) argue that the field of psychology has a lot to offer in terms of human factors related to IT initiatives, yet it appears other fields, such as business management or engineering, are offering more. The authors also note that they could not find many studies on management aspects of IT related implementations. Coburn and Turner (2011) motivate for more shared learnings between researchers from education, assessment and measurement, cognitive psychology, and industrial psychology fields of study. It is easy

to understand why researchers are motivating for more collaboration among research communities when one considers the relevance of statistics, measurement theory, strategy, the psychology of decision making, and management involved in data-driven decision making (Mandinach, 2012).

Rizzuto and Reeves (2007) argue that there have been no systematic research attempts to identify the human factors related to technology related implementations, however, since their publication, some excellent attempts at synthesizing large amounts of literature have been made. See (Raffaghelli & Stewart, 2020), (Ridsdale, et al., 2015), (Sivarajah, Kamal, Irani, & Weerakkody, 2017), (Coburn & Turner, 2011) and (Mikalef, Pappas, Krogstie, & Giannakos, 2018). While these studies have provided improved insight and synthesis on broadly how data-driven organisations are structured and the common barriers they face, especially from a Big Data analytics perspective, they do not provide sufficient insight with respect to the ideal or necessary mindsets and behaviours of senior decision makers.

Lastly, authors from multiple research and industry disciplines agree that there is a dearth of skilled individuals available in the labour market (Alharthi, Krotov, & Bowman, 2017; McAfee & Brynjolfsson, 2012; McKinsey & Company, 2018; UNCTAD, 2018) and that basic and tertiary education institutions need to work harder at intentionally cultivating 21st century skills, including data analysis capabilities (Niebel, Rasel, & Viete, 2019; Tambe, 2014; The Economist Intelligence Unit, 2013). The rapid development of IT technologies and data applications has meant that educational institutions and labour markets have not been able to keep up with private sector demand, with up to 70 per cent of organisations reporting difficulties in filling their data use related vacancies (The Economist Intelligence Unit, 2013; UNCTAD, 2018).

As mentioned earlier in this chapter, data-driven decision making involves the simultaneous application of aspects from various fields of expertise (e.g., statistics and marketing) which is why data scientists who can bridge the gap between business questions and data opportunities are in such high demand (McAfee & Brynjolfsson, 2012). In addition to a tight and challenging labour market for technical data analytics skills, finding executives that understand, and are open to, a data-driven way of decision making is also challenging since many executives performed well using mostly experience and intuition, and now need to pivot to a world where data may challenge some of their

strongly held assumptions (McAfee & Brynjolfsson, 2012; Ransbotham, Kiron, & Prentice, 2015; The Economist Intelligence Unit, 2013).

To summarise, organisations across most industries are investing in data use strategies, however, only a small percentage of these organisations are achieving their desired outcomes. It appears that the critical challenges or constraints organisations are facing are mostly *people* related, and not *technology*, *financial* or *process* related. Challenges include (i) clearly articulated strategies and plans by executives for how data will be used to achieve business objectives, (ii) vague definitions, understandings and expectations with respect to data-driven decision making across different roles and levels within organisations, (iii) difficulty in building an organisation-wide culture of data use, and (iv) a lack of skilled talent in the labour market. All these, and some other, challenges ultimately result in the unsuccessful adoption or application of technologies and processes aimed at deriving actionable insights from data, thus leading to disappointing or delayed returns on investments into these data strategies and interventions.

2.2 The mindsets and accompanying behaviours of data-driven leaders

The following paragraphs look into the key findings of recent literature investigating data use strategies, challenges and other insights. This brief review will highlight how most literature focuses on the structure of the organisation, skills, application of technologies and other barriers to becoming a data-driven organisation. This chapter will also show how very little is said about who decision makers need to be or how they should behave in order to overcome many of the barriers to becoming data-driven that were identified in the literature.

Niebel, Rasel and Viete (2019) use a large firm level survey of approximately 4,400 manufacturing firms to analyse how a firm's level of innovation is impacted by its use of Big Data analytics. The authors find that adopting Big Data analytics is associated with higher levels of innovation in terms of frequency and sophistication. Their study finds that when firms invest in IT specific skills there is a statistically significant and positive relationship between a firm's propensity to innovate and Big Data analytics. While their study highlights how important it is for firms to hire or develop the right IT and data

capabilities, the authors do not investigate factors related to firm leadership. For example, were there any leadership related insights into what differentiated those firms that did develop the identified capabilities?

Ransbotham, Kiron and Prentice (2015) use a case study and survey approach to illustrate and discuss the challenges managers face when having to adjust their methods and practices after the introduction of data-driven insights. The survey collected data from over 2,700 executives, managers and data analytics experts from firms around the world. The authors find that decision makers (managers) struggle to translate analytics into actionable insights for multiple reasons. The authors highlight two reasons why managers struggle to act based on data. These are (i) the speed at which techniques and technologies are advancing, and (ii) finding the time to practise data-driven decision making. The authors provide five recommendations for what managers can do to help them feel more comfortable making data-driven decisions, however, the recommendations are not supported by empirical research and are more focused on domain knowledge and technical skills.

Nevertheless, some inferences can be made regarding what knowledge is needed to lead a data-driven organisation. Their research only covers one small aspect of the larger data use framework and does not cover aspects like the mindsets or dispositions that should be adopted by managers. In fact, this paper argues that, perhaps, the five recommendations Ransbotham, Kiron and Prentice (2015) make would not be necessary or would be naturally addressed if the managers exhibited the mindsets of data-driven decision makers.

Wixom, Yen and Relich (2013) adopt a case study approach to demonstrate the benefits of adopting business analytics. The authors emphasise two themes, *speed* and *pervasive use*, which they argue unlock the maximum benefits from business analytics. The research is targeted at senior decision makers within IT roles and highlights some of the important components or business-units organisations need to establish in order to unlock the benefits of business analytics. However, the types of senior decision makers required or the beliefs these leaders should hold, even if only within IT, is not explicitly discussed.

Barton and Court (2012) provide insights based on previous Big Data project experience. The authors aim their findings at senior decision makers who want to lead more data-

driven organisations. Unfortunately, the article does not employ empirical investigations. The authors do highlight some of the critical organisational components that business leaders need to address to ensure they realise their data strategies which helps in identifying what leader need to *know* and *do*. For example, the authors state that a clear strategy for how data insights will be used to compete is important. From this we can safely infer that business leaders need to know how data analytics can be used to compete and what success looks like. However, Barton and Court (2012) do not explicitly mention or consider the types of mindsets and accompanying behaviours that these leaders need to have in order to implement the necessary actions.

Sivarajah, Kamal, Irani and Weerakkody (2017) implement a systematic literature review to (i) identify relevant research and (ii) synthesise findings. The authors ultimately end up reviewing 227 articles, from 2009 to 2015, relating to Big Data challenges and the analytical methods adopted by organisations adopting Big Data strategies. From the authors research two frameworks are established and key organisational components (e.g., infrastructure, process or management) identified. These insights assist in highlighting what leaders need to know about adopting data-use strategies and where common challenges are likely to arise. Overall, however, the authors do not provide insights on which barriers are more or less relevant, and the focus of the research is more about *data* than *data-use* or *data-driven decision making* challenges. The authors themselves agree that more research into the organisational management aspects of Big Data is required.

Posavec and Krajnović (2016) focus on non-technological challenges that organisations face when implementing their Big Data or data-use strategies. The authors do not adopt a strong research approach and do not collect any primary data; however, they do provide insights on specific management barriers at a level of granularity that other research articles ignore. These more granular insights are also aimed at senior decision makers and are, therefore, more relevant for the target audience of this research. Unfortunately, no leadership mindset attributes are mentioned or investigated.

Coburn and Turner (2011) present a framework with respect to data-use interventions within the education environment. Their presented framework and subsequent propositions are based on a review of 161 research articles, books and reports. The authors also provide insights into the drivers and interactions of each framework

component put forward, highlighting the necessary skills and activities of relevant participants. The research indeed highlights the important role that managers and leaders play in realising the objectives of certain components (e.g., establishing routines, effective data norms, cultures and politics) which is helpful in understanding what leaders need to know and focus on. However, Coburn and Turner (2011) do not discuss or identify necessary leadership traits, beliefs or mindsets. While the research does cover the important roles certain participants must adopt and the broader objectives of data-use interventions in education, the research does not delve into the type of leaders or managers that are required or the type of mindsets needed to fulfil these roles. This, like most current literature on Big Data and data-use, leaves a void in terms of what is holistically needed by organisations (in any sector) from their leaders to realise their organisational data-use objectives.

Alharthi, Krotov and Bowman (2017) review key implementation and management barriers related to data-use interventions and then provide four tactics for addressing these barriers. The researchers adopted a case study approach and then used insights from McAfee and Brynjolfsson (2012) to further investigate identified barriers. By highlighting and further unpacking such barriers the authors provide, like other authors, insights into what leaders and managers need to be aware of and what actions may help overcome these barriers. The authors do not provide any insight into which organisational role-player is responsible for addressing any barriers identified nor what type of leaders are best suited to avoid or overcome these barriers. As with many of the studies reviewed here, the authors do not investigate beyond the key organisational components required to create a data-driven organisation and associated barriers. The research is helpful in identifying what leaders should be aware of, and therefore, what they should know about and some solutions, although not empirically tested.

McAfee and Brynjolfsson (2012) is a highly referenced article (see Mishra, Luo, Jiang, et al, (2017)) focusing on leadership and management issues related to data-driven organisations. The authors rely on case studies and structured interviews they ran with executives from more than 330 American organisations. The authors highlight the important roles executives play in transforming and leading data-driven organisations, what they have to do and what they need to embrace if they want to succeed in their data-use or Big Data transformations. The authors discuss (in more detail than the other

authors reviewed in this paper) the challenges senior decision makers will face, particularly when it comes to embracing a new way of decision making that may challenge strongly held beliefs. These important insights and discussions allude to the importance of understanding the mindsets, beliefs, attitudes and perspectives of data-driven leaders. While the authors provide valuable insights with respect to the organisational benefits of adopting data-driven decision making and what leaders need to know and address, they do not investigate leaderships traits, like mindsets, necessary for overcoming the barriers or achieving the objectives they highlight.

Finding research on the mindsets or characteristics of data-driven leaders is challenging and likely due to the topic not being sufficiently investigated. However, finding research and literature on the characteristics and mindsets of leaders in general is not problematic. For example, Kouzes and Posner (2019) use 2,280 performance reviews of managers to investigate if managers with a growth mindset exhibited more or less behaviours associated with leadership than managers with a fixed mindset. Their research and findings illustrate that (i) the mindset of a manager influences their leadership behaviours, (ii) that the mindset of a manager or leader influences the mindset, motivation and performance of other members of an organisation, and (iii) that the mindset of an individual influences whether they will be willing and able to learn new skills and competencies. This has important implications for leaders who want to drive a new way of decision making in the organisations they lead and manage, especially since their own mindsets and behaviours have such a strong influence on other members within the organisation. Their research has two shortcomings with respect to the objectives of this research. The first is that Kouzes and Posner (2019) do not explore or define mindsets outside of the two main mindsets: a *growth mindset* or a *fixed mindset*. The second is that the authors explore mindsets across any type of organisation and, therefore, do not provide any insights with regards to leaders of data-driven organisations.

In summary, existing research sufficiently addresses the necessary organisational components of data-driven organisations. This assists leaders in identifying what investments or changes are needed, within their organisations, so that the right foundations for data-driven decision making are in place. For example, many of the research articles reviewed above highlight how important it is to have the right data storage and processing solutions in place so that data analysts (or data scientists) can

efficiently and safely derive actionable insights from these data assets. Some consolidation of research is necessary because most articles reviewed here tend to cover only a subset of all the necessary components. So, *what* senior decision makers need to know (e.g., skills, culture and leadership are important) is generally well researched, including the typical barriers associated with these components (e.g., cultivating a data-driven culture or finding the right talent).

Current literature on data-driven decision making tends to focus more on the nuances and challenges of Big Data, while ignoring or not explicitly mentioning data-driven decision making in general. This is not a major issue since most of the findings are relevant for any type of data-driven decision making (regardless of the size of the source data) but it is still worthwhile mentioning the insight in case there are findings relevant only to one type or size of data.

Lastly, and most importantly for this research, current literature does not provide sufficient insight into the mindsets of data-driven leaders. The literature reviewed in this paper does refer to what leaders need to know and in some cases do, however, this alone will not help leaders understand what mindsets and accompanying behaviours they need to practice and adopt to (i) become more data-driven themselves, and (ii) to cultivate a data-driven culture within the organisations they lead.

2.3 Qualitative attributes key to the research

Identifying and discussing the following attributes will be critical in answering the research questions of this investigation and ultimately in achieving the objectives of this research. The specific organisational components that are necessary for an organisation to become and be a data-driven organisation. Identifying these components is important in providing a framework against which different mindsets and behaviours may be required. Having a full view of all the necessary components (or business units) identified by previous research will also reduce the risk of not gathering sufficient data when conducting interviews.

The mindsets and associated behaviours of leaders and specifically, the mindsets necessary to implement the necessary components and processes of data-driven organisations and the mindsets necessary to avoid or overcome the typical barriers or challenges leaders face

when implementing data-use interventions or strategies. This will include gathering information on beliefs, attitudes and motivations leaders who have successfully led or are leading data-driven organisations.

Before we can start investigating further these attributes we need to better understand where and how these attributes may improve data-driven decision making. To ensure a robust assessment and review processes we need to first understand the theories or frameworks within which organisational data-driven decision making takes place.

2.4 Data use theories and intervention frameworks

Identifying relevant data use frameworks will support this research by allowing all insights gained during the data gathering phase to be placed within the domain of data-driven decision making, thereby validating the relevance of those insights. This also facilitates an improved understanding of the mechanisms through which identified mindsets and behaviours lead to or overcome the common barriers to effective data-driven decision making identified within the literature research. These frameworks also help senior decision makers and practitioners identify what they need to know, in terms of the components of data use interventions, and how data-driven decision making starts with data and ends with desired outcomes.

2.4.1 Framework 1: The data-driven decision making process

Sivarajah, Kamal, Irani and Weerakkody (2017) provide multiple frameworks related to challenges, processes and components of data-driven organisations or data-driven decision making. Given that the topic of this research falls within the domains of data-use and leadership, it will be helpful to first define the data-driven decision making process so that all subsequent issues discussed here can be placed within this process and, therefore, discussed with relevance. Furthermore, understanding the data-driven process is important because leaders have different roles and responsibilities across the process. Figure 1 below is sourced from Sivarajah, Kamal, Irani and Weerakkody (2017) and illustrates the phases that take place when information is used to ultimately drive actions. For example, a leader's role within the *information* phase may relate to investing in the right security solutions while in the *decision* phase it may be making a final call on which decision or option is preferred based on the organisation's overall strategy.

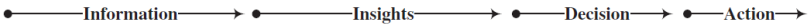


Figure 1: Classification of types of big data analytical methods, reproduced from Sivarajah, Kamal, Irani and Weerakkody (2017)

Tabesh, Mousavidin and Hasani (2019) provide additional phases to the data-driven decision making process illustrated in Figure 1 above. The authors argue that once actions have been taken that outcomes will occur and regardless of the success or failure of these outcomes, new knowledge will be gained (Figure 2). The authors argue that this new knowledge gained will influence future data-driven decisions.

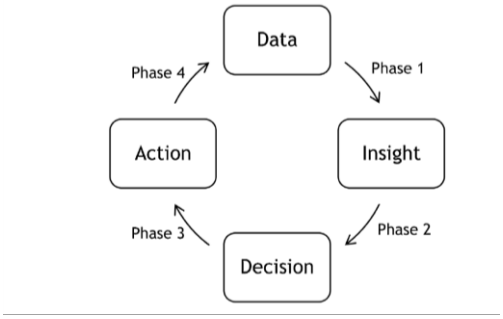


Figure 2: Big data analytics cycle, reproduced from Tabesh, Mousavidin and Hasani (2019)

The data-driven decision making process can be further expanded by the recommendations put forward by Mandinach and Gummer (2016). Here the authors highlight that data-driven decisions originate from some problem statement or question. In other words, the gathering of data and subsequent analysis work is not done in a vacuum. The authors also argue that data first needs to be transformed into information (Figure 3).



Fig. 1. Conceptual framework for DLFT.

Figure 3: Conceptual framework for data literacy for teachers, reproduced from Mandinach and Gummer (2016)

Lastly, Coburn and Turner (2011) provide one more phase of the data-driven decision making process which will prove helpful when discussing what leaders need to know and

what role they play is addressing common barriers. Figure 4 below is the authors representation of a data-use intervention framework within the education sector. They highlight that during the data-driven decision making process, decision makers will first construct multiple implications (or multiple options with potential outcomes) before deciding (the decision phase) on which option to follow-through on (the action phase).

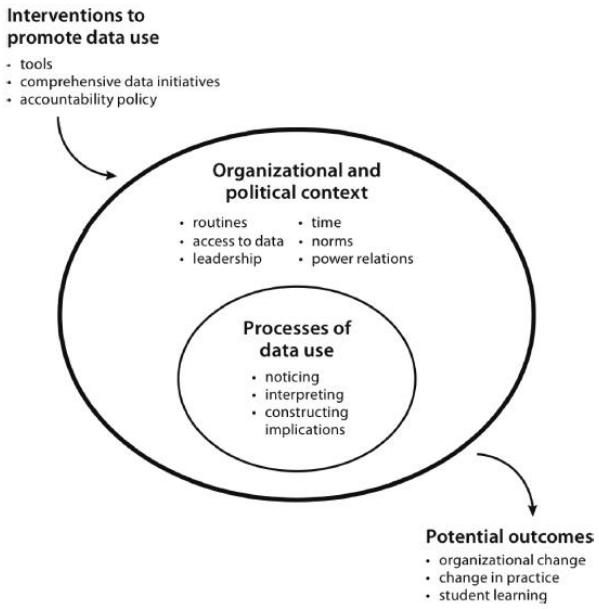


Figure 4: Framework for data use, reproduced from Coburn and Turner (2011)

Combining the phases highlighted by Tabesh, Mousavidin and Hasani (2019), Sivarajah, Kamal, Irani and Weerakkody (2017), Coburn and Turner (2011) and Mandinach and Gummer (2016) results in the consolidated data-driven decision making process in Figure 5 below that this research will adopt to frame and position subsequent discussions and research insights.



Figure 5: Consolidated data-driven decision making process.

2.4.2 Framework 2: The components of a data-driven organisation

Adrian, Abdullah, Atan and Jusoh (2018) provide a comprehensive and current overview of the components of a data driven organisation as well as a number of supporting factors which provides for a sound base on which to overlay important issues senior decision

makers need to address and more specifically the mindsets required to realise the intended objectives of these components (Figure 6). The authors applied a systematic literature review approach to craft their final framework which illustrates three core components generally found in other similar and earlier studies. These components consist of (i) physical and digital technologies, (ii) organisational processes and strategy, and (iii) people skills and culture. The issue of leadership mindsets is relevant across all three of the organisational factors defined by Adrian, Abdullah, Atan and Jusoh (2018) because leaders play an important role in implementing and realising each of these components. Emphasis will, however, be given to the *organisation* and *people* dimensions (Figure 6) because the prevalent *people* related barriers and challenges that firms are struggling to overcome reside within these two components.

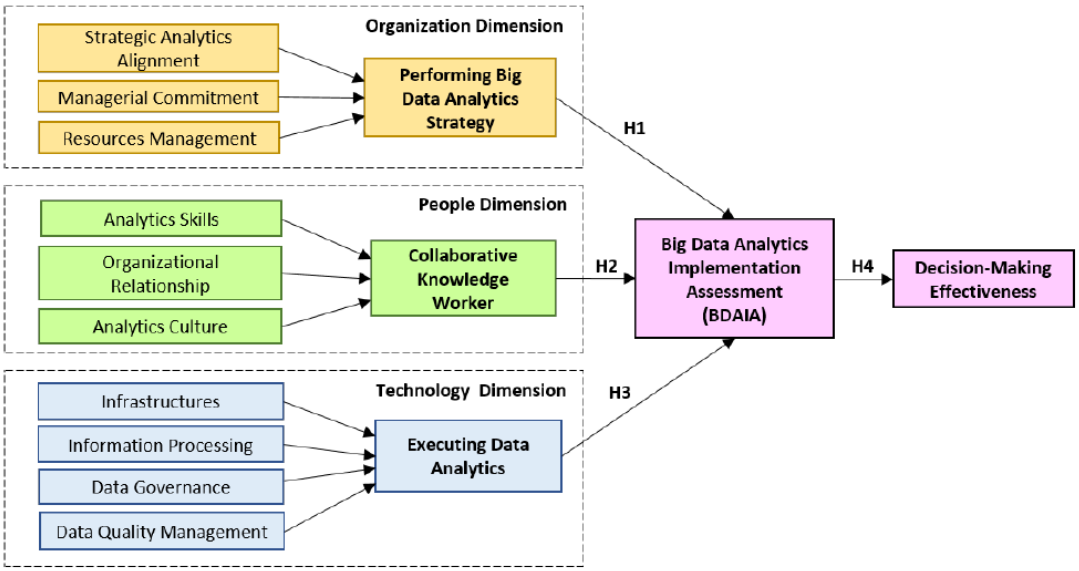


Figure 6: Conceptual model BDA implementation assessment effect on decision-making, reproduced from Adrian, Abdullah, Atan and Jusoh (2018)

2.5 Summary and conclusion

2.5.1 Summary of literature reviewed

Organisations across most industries are investing in data use strategies, however, only a small percentage of these organisations are achieving their desired outcomes. It appears that the critical challenges or constraints organisations are facing are mostly *people* related, and not *technology*, *financial* or *process* related. Challenges include (i) clearly articulated strategies and plans by executives for how data will be used to achieve business objectives, (ii) vague definitions, understandings and expectations with respect to data-driven decision making across different roles and levels within organisations, (iii) difficulty in building an organisation-wide culture of data use, and (iv) a lack of skilled talent in the labour market. All these, and some other, challenges ultimately result in the unsuccessful adoption or application of technologies and processes aimed at deriving actionable insights from data, thus leading to disappointing or delayed returns on investments into these data strategies and interventions.

2.5.1.1 Knowledge gaps

Of importance to this research is that current literature does not provide sufficient insight into the mindsets and behaviours of data-driven leaders. The literature reviewed in this paper does refer to what leaders need to know and in some cases do, however, this alone will not help organisations and leaders understand what mindsets and accompanying behaviours they need to practice and adopt to (i) become more data-driven themselves, and (ii) to cultivate a data-driven culture within the organisations they lead.

This research paper will investigate the mindsets and associated behaviours of leaders and specifically, the mindsets necessary to implement the necessary components and processes of data-driven organisations and the mindsets necessary to avoid or overcome the typical barriers or challenges leaders face when implementing data-use interventions or strategies. These insights will be discussed within the domain of two broader frameworks, that is: (i) the data-driven decision making process, and (ii) the structure of a data-driven organisation. These frameworks will place research insights within the domain of data-driven decision making and thus helps interpret and better understand

the mechanics through which identified mindsets and behaviours overcome common barriers to effective data-driven decision making.

2.5.2 Proposed research strategy, design, procedure and methods arising from the literature reviewed

To address the knowledge gaps identified in the literature review above this research paper aims to gather qualitative insights on the mindsets and accompanying behaviours of senior decision makers and leaders who are successfully cultivating data-driven decision making in their respective organisations or who are already leading successful data-driven organisations. Given that no explicit data-driven mindset or data-driven behavioural framework exists (to the best knowledge of this author) an unstructured interview process with experts will be adopted to ensure a wide breadth of insights are allowed for.

3 RESEARCH STRATEGY, DESIGN, PROCEDURE AND METHODS

Introduction

In Section 1.2.3, we have posed two questions that this research report intends to answer—that is, what mindsets differentiate data-driven decision makers from non-data-driven decision makers, and what are the behaviours associated to these mindsets that lead to effective data-driven cultures and data-driven decision making? We have since reviewed literature and developed interpretative and conceptual frameworks, that will guide the choices of techniques we will use. This chapter identifies and describes the research approach, design as well as procedure and methods that we employ in this research to collect, process, and analyse empirical evidence. Broadly, it has three objectives; namely, to identify and describe the research strategy (Section 3.1), the research design (Section 3.2), as well as the procedure and methods (Section 3.3). This chapter also describes the reliability and validity measures (Section 3.4) that this research applies to make it credible as well as the technical and administrative limitations of the choices made (Section 3.5).

3.1 Research strategy

A research strategy describes the approach that has been chosen to ultimately answer the research questions and, therefore, achieve the purpose of the research. According to Bryman (2012) a quantitative, qualitative, or mixed research strategy can be chosen. These are summarised in Table 1 below, followed by a brief discussion and justification of the chosen research approach for this paper.

Table 1: Research strategies

Research strategy	Description
Quantitative approach	Based on the positivist paradigm, quantitative research uses numeric data and predetermined measurements to address research questions.
Qualitative approach	Aligned to the interpretivist paradigm, qualitative research examines problems from their social contexts using soft data rather than numbers.
Mixed methods research	Drawing on pragmatism, mixed methods research uses multiple methods to analyse world problems. This requires mixing of quantitative methods and qualitative methods e.g., interviews and questionnaires for data generation.

From the three types of research strategies mentioned in Table 1 above, this research paper adopts a qualitative research strategy. This form of research strategy involves applying an inductive approach to contextualising research insights and requires the author to provide some form of interpretation for what their findings may imply against (or for) a chosen theory (Bryman, 2012).

The rationale for choosing a qualitative research approach is that the attributes under investigation in this study are "soft" and of a human nature (e.g., knowledge). The objective of this research is to identify particular human attributes (mindsets) and behaviours that reside within the minds of industry experts and not within any existing or potential databases and are not discoverable from some form of numerical technique. A key outcome of this research is an enhanced understanding of the important attributes a leader should possess (e.g., an entrepreneurial mindset) and not an insight into the magnitude of possessing such attributes (e.g., 5 per cent increase in net profit). Therefore, an inductive approach is justified. This is similar to Mikalef, Pappas, Krogstie and

Giannakos (2018) who review existing literature (confined by specific topics, but not research field) to construct a synthesised view on the important tangible components, intangible components and skills related to Big Data analytics. The authors also consult a panel of experts to help guide their research. By applying this approach, the authors are able to leverage off existing literature to quickly build a comprehensive view of what existing research has already provided. This allows them to construct their recommendations and propositions on the back of multiple research findings, therefore, providing the authors and reader comfort that the findings are based on a reliable and comprehensive set of exiting knowledge.

Similarly, this research paper builds on existing literature related to the human factors required for effective data use and achieves this by providing a new perspective, specifically, the perspective of the organisational leader. To achieve this, a strong foundation of existing literature is required in order to construct trustworthy and repeatable findings and recommendations. Industry experts are consulted to further validate findings and any inferences made, and to provide reliable insights for any components that existing literature does not currently address. By adopting this approach, this paper builds a strong foundation for future research that may use larger surveys or firm performance data to further test the findings provided herein. Presented below is the research design applicable to this study.

3.2 Research design

A research design relates to the overall data collection and analysis approach chosen that will best achieve the objectives of the research study in question (Bryman, 2012). There are five main types of research designs. These are, (i) cross-sectional, (ii) longitudinal, (iii) case study, (iv) comparative, and (v) experimental (or quasi-experiments). Of these five research designs this study adopts a cross-sectional design. This is because variation with respect to mindsets is being investigated with the aim to unpack patterns through unstructured interviews. Also, the study focuses on a single point in time and does not investigate trends or impacts of changing mindsets over time, for example.

Kouzes and Posner (2019) adopt a cross-sectional research design in their study that investigates the leadership behaviours of managers who have a growth mindset versus a fixed mindset. The authors selected this design because they wanted to investigate the

patterns between two different types of managers. Their objective was to highlight that mindsets matter when it comes to general leadership behaviours. The benefit of choosing this approach is that they can investigate and highlight their results confidently without their results being compromised by changes in time periods. In a similar way, this research is conducted in a point in time and investigated the mindsets and behaviours of decision makers who are successfully leading data-driven organisations. This research does not investigate trends or the impact of changing mindsets over time. It is envisaged that future researchers will be interested in quantitatively or empirically testing the findings of this research through cross-sectional and longitudinal designs once the findings of this research unlock a (very) new discourse in the broader data-driven decision making and management literature.

3.3 Research procedure and methods

This section documents the actual procedure and the methods employed in this research to collect, collate, process, and analyse empirical evidence. Broadly, we detail the data and information collection instruments (Section 3.3.1), the target population and sampling of respondents (Section 3.3.2), the ethical considerations during the research process (Section 3.3.3), data and information collection process and storage (Section 3.3.4), data and information processing and analysis (Section 3.3.5) as well as the background description of the respondents who provided empirical evidence for this research study (Section 3.3.6).

3.3.1 Research data and information collection instrument(s)

A data collection instrument is defined as a tool or set of tools used for collecting primary data that are necessary for answering the research questions (Bryman, 2012). These tools can be defined within two broad approaches to collecting primary information, that is: observation schedules and interview schedules. Interview schedules have been adopted for the purposes of this study because the attributes of interest relate to cognitive variables that are not easily observed. To gather the necessary data for this research study participants were assisted in providing the necessary insights that this study requires. Explicit feedback from participants with direct and subsequent explanations of their

feedback is more helpful and useful than observations which would need to make inferences and assumptions.

Within the interview research approach there are three categories or scales of structure that can be adopted. These are: unstructured, semi-structured, and fully structured. These structures represent the degree of similarity, and therefore also the potential for broader scope and insights, across a similar data collection instrument. For example, a structured (or standardised) interview is designed in such a way that each survey participant is asked the same questions within the same context to ensure a high level of comparison across all survey participants (Bryman, 2012). While an unstructured or semi-structured interview schedule, or interview guide, allows for more open-ended responses and additional discussions based on a participant's responses.

The attributes relevant to this study (e.g., leadership mindsets and behaviours) may not be common topics of target participants and existing literature on the mindsets of data-driven leaders is scarce. For this reason, a semi-structured interview approach was adopted to allow for tailored questioning and to ask wider follow-up or probing questions that may not have been considered based on existing literature.

Overall, this research paper adopts a semi-structured interview schedule to collect primary data regarding the mindsets and associated behaviours that leaders need to possess in order to cultivate effective data-driven decision making within their respective organisations. Questions included in the semi-structured interview guide are based on the two main frameworks discussed in Section 2.4, the research questions provided in Section 1.2.3 and key themes identified in the literature review in Section 2.

3.3.2 Research target population and selection of respondents

3.3.2.1 Research target population

A target population is a sub-set of units (e.g., people, organisations or documents) that contain relevant information related to the research questions being addressed (Bryman, 2012). While the focus of this research is the leader of an organisation and, perhaps in larger organisations, other executives, the target population for the data gathering phase is somewhat broader because important insights can be gathered from those that report

directly to, or work directly with, senior decision makers. For this reason, the target population for the semi-structured interviews in this research are (i) senior decision makers or leaders of data-driven or data-intensive organisations, (ii) data scientists that report directly to executives or leaders within the c-suite level, and (iii) experienced practitioners that help organisations implement and realise their data-use strategies (e.g., directors of data analytics or management consulting companies).

The participants of this research have experience and, therefore, insights with respect to the characteristics of senior decision makers who have successfully or unsuccessfully led data-driven organisations. These insights provide the foundations for a new area of study within the broader data-use and management discourse. As demonstrated in the literature already reviewed above, previous surveys and interviews did not explore or probe leadership mindsets and behaviours necessary for effective data-driven decision making, yet these insights reside within the participants of this research.

3.3.2.2 Sampling or selecting respondents from the target population

After a target population has been identified the spread and quantity of the target population must be decided which refers to the sampling of the target population. Purposive sampling within qualitative research, also adopted in this research, refers to the non-random sampling of survey participants so that there is intentional control over who or what is being surveyed or observed (Bryman, 2012). Purposive sampling is appropriate and ideal for this research because specific designations (e.g., head of analytics or chief information officer) from data-driven organisations (e.g., banking, insurance, engineering, etc.) form part of the target population. For this reason, it makes sense not to survey random staff members of an entire organisation or CEOs from any organisation or industry.

Secondly, the purpose of this research is not to prove or measure a representative sample of any sort across an entire geography or industry. Therefore, the appropriate sample size can be defined by minimum exposure of target population participants. For this reason, at least two participants are interviewed within each of the three categories of the target population: (i) senior decision maker within a data intensive organisation such as the head of a business unit or at the director level, (ii) a data scientist that reports directly to c-suite

individuals, and (iii) an individual that is or has worked as a consultant or specialist within an organisation that helps other organisations implement their data-use strategies.

Implementing semi-structured interviews with each of the three types of target population participants allows for a broader scope of insights with regards to what data-driven mindsets leaders need to possess and the typical behaviours they exhibit. This also allows for some pattern and theme identification.

3.3.3 Ethical considerations when collecting research data

Research ethics has to do with the integrity of the research and the respect given to participants being studied, observed or interviewed (Bryman, 2012). Ethics in research generally revolve around four themes: harm to participants, informed consent, privacy and transparency (Bryman, 2012). Conducting research ethically is important for current and future research. If the broader public perceived the research community as disrespectful, flippant, or unconcerned about the safety or privacy of participants, then future researchers will find it difficult to find willing research participants. Ethical research practises also ensue that research participants provide accurate information which enhances the overall quality and validity of research findings (Bryman, 2012).

The author of this research paper is a manager of a country-wide data-use project that aims to improve decision making within the basic-education sector in South Africa. The interest in data-driven decision making by the author is driven by the successes and challenges faced on the project. Through this research the author hopes to help other organisations overcome or avoid the most challenging barriers to realising the full potential of data-driven insights.

3.3.3.1 Informed consent

All interviews commenced with discussion of the background to this research project, highlighting that this research is part of the authors MBA study requirements and that the author is a manager of a large data-use project. The objectives of the research and interview was explained, and participants were informed that their identities will be anonymised within the research report.

3.3.3.2 Confidentiality

The interview, data collection and data management processes were explained to each participant before each interview commenced. No participant expressed any concern or request to not proceed. All information is stored on the authors personal computer which is encrypted and password protected. No audio, video or transcripts with personally identifiable data will be shared, except for MBA assessment purposes with the authors supervisor. All interview participants were made aware of this.

3.3.3.3 Voluntary participation

For transparency purposes the interview guide was shared with willing participants before any interviewing commenced. This gave participants an opportunity to assess the nature of the interviews before committing to participate. No participants chose to not answer any questions and no participants decided to end the interview prematurely. Participants were made aware that if they did decide to pull out of the research that they were within their rights to request all data, references and proof of the interview to be destroyed if they felt that the interview was not conducted as promised. In respect of the participants time, no interview lasted longer than 90 minutes and participants were all given the option of splitting or extending interviews if they wished to do so. Interview questions only commenced once verbal consent to be interviewed was given and then recorded using audio recording.

3.3.3.4 Safety precautions

Participants were asked to conduct interviews virtually in light of the COVID-19 pandemic. Only one participant requested that a physical interview be held instead, in which case the interview was held outdoors and in accordance with all Lockdown regulations at the time of the interview. Virtual interviews were conducted using Google Hangout.

3.3.4 Research data and information collection process

The process of collecting data can be achieved through five main approaches: interviews, focus group discussions, document or content analysis, ethnography (or observations) or conversation analysis (Bryman, 2012).

For the purposes of this research, live interviews were conducted, predominantly virtually. The conversations of these interviews were recorded (with the consent of each participant) and then transcribed for deeper analysis.

The benefit of adopting live interviews is that the researcher can ask follow-up probing questions during the interviews in a setting which should make the participant feel comfortable. Additional insights and opinions were gathered from the experts being interviewed which would not have been possible through alternative approaches such as structured surveys or interviews.

Once the interviews were recorded (through audio recordings) the conversations were transcribed to digital text. Recordings were transferred and stored on my personal computer which is password protected. Content is not being stored on any external hard-drive and no personal names or identifiable information has been saved in the transcripts or research report.

3.3.5 Research data and information processing and analysis

3.3.5.1 Research data and information processing

A thematic analysis approach is adopted to process the information gathered from the interviews. Thematic analysis involves structuring qualitative data within a matrix structure against an already defined set of themes – in this case the themes or categories are the organisational components contained within the conceptual frameworks illustrated in section 2.4 and based on common themes emerging from the interviews. This approach assists in structuring interview insights gained, i.e., feedback on the mindsets and behaviours of successful data-driven leaders, in such a way that these insights across all interviews can be synthesised and grouped against the key concepts already identified and discussed within the literature review. I then investigate and highlight any similarities that bring validity to the findings or differences that result in inconclusive or weak inferences.

3.3.6 Description of the research respondents

For the purposes of anonymity, no names of any of the participants have been provided in Table 2 below. All participants work in South Africa.

Table 2: Description of interview participants

Participant	Description
Interview participant A	Participant A is a data operations and technology expert with experience in business analysis, business intelligence, business analytics, systems development and process improvement. Participant A has over 15 years of working experience, two of which were in a Chief Information Officer role.
Interview participant B	Participant B's background is in quantitative microeconomics and econometrics; however, Participant B is now a founder and the chief executive officer of an independent consulting firm specialising in data science, big data and machine learning. Participant B has over 15 years of experience in quantitative analytics and leadership.
Interview participant C	Participant C has a background in macroeconomics, econometrics and economic research. Since 2015 Participant C has been working on a large data transformation project within the basic education sector. Participant C is now a director at an independent economics advisory firm in South Africa.

Interview participant D	Participant D is the head of data at a large national bank and has over 12 years of experience in business intelligence, analytics, strategy, innovation and holds both an MBA and computer science degree.
Interview participant E	Participant E is a data scientist specialising in artificial intelligence, machine learning and the broader data science space. Participant E is a co-founder of a technology product development company and has over 15 years of experience in data analytics, data management, digital innovation, and data science.
Interview participant F	Participant F heads up the actuarial department at a large insurer known for its data driven approach to innovation and customer service. Participant F has over 15 years of experience in the insurance and data analytics domain.

3.4 Research strengthens – transferability, credibility, and dependability

The term transferability within the domain of research refers to the degree to which the findings of a research report apply to other contexts (Bryman, 2012). To ensure insights gained are transferable, interview questions are posed in a general manner and not industry or location specific. Participants operate across different industries and have work experience from different industries, which ensures feedback is non-industry specific. In the case of this research, the findings appear to be transferable across industries (e.g., finance and manufacturing) and there is no indication to suggest non-transferability across geography. However, it is noted that a potential weakness of this research is that all participants operate within South Africa, and therefore, transferability

across geographies cannot truly be asserted. The broader topic does reside within the organisational setting of decision making, that is, the findings are not transferable to data-driven decision making within the homestead for example.

The term credibility within the domain of research refers to how believable, or trustworthy, the findings from the data gathering process are (Bryman, 2012), and therefore, selecting an appropriate target audience for interviews is important. Participants of this research project have extensive experience in data-driven decision making themselves and in support of key decision makers. This improves the credibility of interview participant feedback. Secondly, the research paper highlights where participants give similar feedback or where existing literature hints at similar findings (i.e., triangulation), thereby further increasing the credibility of insights, since interviews were conducted independently.

The term dependability within the domain of research refers to how consistent the findings are over time or how much are the findings expected to change over time (Bryman, 2012). The findings of this research are most likely not applicable to historical periods since various aspects of a data-driven organisation may not have been possible. The dependability of findings for future periods is not tested, however, given that Big Data and leadership within a data rich world are emerging fields of study, the findings are likely to be relevant for the foreseeable future, until such a time that data is no longer a valuable input into decision making.

3.5 Research weaknesses – technical and administrative limitations

The author recommends that future researchers address some of the weaknesses of this research paper by (i) interviewing a larger and more diverse sample of participants from different genders, geographies and industries, (ii) include a portion of structured interview questions to allow for some tests of similarity and perhaps ranking of feedback across interview participants, and (iii) include case study research that discusses successful and unsuccessful data transformation projects.

3.6 Conclusion

The research strategy, design, procedures and methods were discussed to illustrate how the study was executed methodologically. Chapter four follows with presentation of the research findings.

4 PRESENTATION OF RESEARCH RESULTS

Introduction

This section presents the findings extracted from the interviews with the six experts. Interview participants were asked about their perspectives and opinions with regards to data-driven organisations and the role senior decision makers play in such an organisation or the role they play in transforming organisations into data-driven organisations. The implication of these findings will be discussed in Section 5 and then summarised in context with the literature review findings to construct the conclusions and recommendations presented in Section 6.

This chapter presents the key findings gathered from the unstructured interviews with the six participants who have significant experience in using data derived insights to make decisions. Section 4.1 is divided into three sub-sections. The first sub-section (Section 4.1.1) presents the findings from the expert interviews which validate or expand some of the findings from the literature already reviewed in Section 2. The second sub-section (Section 4.1.2) presents the findings mentioned by more than one of the six interview participants and the third and final sub-section (Section 4.1.3) presents findings that were unique to only one participant.

4.1 Findings that support literature already reviewed

The aim of the six interviews was not to validate or further investigate findings from the literature already reviewed, however, highlighting the instances where such supporting comments are provided offers additional confidence in the literature review findings and understanding of the broader problem statement, theoretical frameworks and context defined by the literature review. The two key findings here relate to the important role senior decision makers play and that organisations are indeed struggling to implement data-driven decision making as soon or as effectively as they had hoped to.

4.1.1 Companies are not realising their expected benefits

Existing literature reviewed in Section 2 of this research paper highlights that most organisations are not realising the benefits of their data use investments fast enough or at

all. Participant D confirms this with "Companies have pumped in hundreds of millions of Rands into projects for data, and it has not been delivered. As in more than one company I have worked for. Because they have had the wrong leaders in place" which also highlights the importance of having the right decision makers in place. Similarly, Participant E also highlights the difficulty in making progress and highlights the importance of the right culture "So we, I would say, I've been here for three years, we have nowhere near achieved, what was the promise of why I was hired. Nowhere close. Why? Because it's not the culture". Lastly, Participant F also mentions his experience in working in different firms and provides some perspective on why some organisations struggle to realise the benefits from their data transformation investments, noting that "And then, oftentimes, projects go into this kind of deep hole and then you don't actually see the benefits of it until many years and so your payback period is quite far out, if you even reach them".

4.1.2 Senior decision makers influence strategy, talent and culture

All participants mentioned the important role of decision makers with regards to (i) creating a clear data use strategy, (ii) realising the objectives of that strategy through organisational change and talent acquisition, and (iii) influencing the organisational culture with respect to data use.

Participants emphasised the importance of an organisation strategy that clearly illustrates how senior decision makers anticipate data will be used to achieve specific business objectives. For example, Participant A states "I think that's the key to it. Align to your strategy. Ultimately it has to serve a purpose more so than anything else". This aligns strongly with the second framework presented in Section 2.4.2 which emphasises the importance of strategic analytics alignments within the *Organisation Dimension*. Without a clear plan defined and spearheaded by senior decision makers, data related activity, such as the management of data to data analysis, will be carried out in a sort of vacuum misaligned to the larger organisational objective, resulting in certain specialists becoming frustrated and slow decision making by senior decision makers. The issue of a clear data use strategy and plan also relates to the data-driven decision making process presented in Section 2.4.1 which highlights that data-driven decision making starts with a clear problem

statement or question which then guides research and data analysis activities, as well as define what success looks like. Participant F highlights,

> "and I mean, again that speaks to having the right direction and when translating those insights into action that becomes the guiding force and leaders have a critical role to play in that. So that's how it happens at [removed]. I haven't seen it happen like that anywhere else".

In addition to a strategy that clearly defines how data will be used to realise organisational objectives, decision makers must also understand which specialists to hire to realise those objectives. Hiring the wrong specialists will lead to frustration and decision making inertia. As Participant E states "That's why he's the CEO. So, it's like…we're doing this vision this way…And then you have a very, very strong technical operations level, who then hire accordingly and implement the vision." Similarly, Participant D mentions the role senior decision makers make when it comes to hiring the right talent "it's the senior management. And when I say senior management, I'm talking about the executives and people who make the decisions for appointing data people". Participant D also expands on the importance of hiring the right talent by giving personal experience of where hiring decisions went wrong. He states, "What organizations are doing now is that they are hiring data business analysts and all these data analysts in senior roles because the techies don't have these communication skills…They hire more under relatability" and elaborates on what can happen if the wrong talent is hired, "so you have the wrong people driving and what happens is it creates a reactive environment, rather than a proactive environment".

Lastly, senior decision makers influence organisational culture. Participant A states "…a culture like this is not created without top leadership". The way in which the leadership team behaves, especially in the way they make decisions, influences how the broader organisation behaves. For example, if decision makers like a data-driven approach, this will influence how the data and marketing team operate. Participant F states "and I've seen the differences in leadership styles, particularly right from the very kind of senior-level of leadership and how that kind of permeates into the organization and what it does to culture". And Participant A states, "Culture, values. All of that boils down to behaviour". And culture matters a lot, again to reproduce what Participant E stated above, "I've been here for three years, we have nowhere near achieved, what was the promise of

why I was hired. Nowhere close. Why? Because it's not the culture". Similarly, Participant F states, "the data landscape and … evolution of a company's data competency or asset, I think,… it's very much driven by the leadership and the culture of the company" Participant F.

To summarise, senior decision makers are critical in helping organisations realise the benefits of being more data-driven. This aligns with the key findings from the literature reviewed and strengthens the argument that more needs to be done to understand what exactly are the ideal or preferred attributes of decision makers leading organisations that aim to be more data-driven? As Barton and Court (2012) state "Adjusting culture and mind-sets typically requires a multifaceted approach that includes training, role modelling by leaders, and incentives and metrics to reinforce behaviour". Decision makers need to understand the importance of these findings if they want the broader organisation to be more data driven. However, this is easier said than done. Participant B reflects on past implementation work "but, doing the behavioural change is very difficult". Section 4.1.2 and 4.1.3 dive deeper into the mindsets and behaviours of decision makers that are effective in defining and realising data use strategies and in cultivating the desired behaviour changes and ultimately culture of data use.

4.2 Common findings across interviews

In this section the insights related to the ideal attributes of leaders is discussed and why such attributes are important.

4.2.1 Leaders as advocates and role-models for data use

Interview findings suggest that senior decision makers need to repeatedly champion the use of data when making decisions. As Participant A states, "Preaching from the same hymn sheets. Over and over and over and over and over. And over again, until people come around, or get tired of listening to what you've been saying". Participant D stresses the importance of being an authentic advocate, with a passion for data, relating back to individuals he has worked with that struggled to understand the data-driven decision making process. He states, "I think passion is also a piece you need to add in there…You have to have a passion for data because it is a boring area… from a third-person point of view". Participant D also emphasises that the term data-driven might not mean the same

thing to everyone, "data is something you can't see and it's often thought of as a very simple concept. So, people would be like, oh, data Excel worksheet, okay I need a report".

A recurring theme is that of action by decision makers or the intention of action. Interview participants stressed that decision makers must truly want to act based on data derived insights if they want others to adopt a similar approach. Participant A states, "Align to your strategy. Ultimately it has to serve a purpose more so than anything else. You can tell people a lot of interesting things about their data, but interesting doesn't actually drive any action". Participant F highlighted this too by illustrating how leaders, through their behaviours regarding the use of data, influenced how decision making is now conducted in the organisation which he considers as truly data driven, he explains "And so you know that's how it is. Come with the data first and then we kind…you know, discuss the possibilities and then make a decision from there".

Findings also suggest leaders need to demonstrate and communicate the benefits of adopting data. Participant A explains how he did this successfully through sharing relatable examples, he states "kind of giving them real world examples in their own spheres, that kind of started making it almost more tangible for them, almost more real…they could see it. They could see the value in it…easier than they could before". Similarly, Participant B explains "you implement on a small scale and you have a sort of a counter factual group or control group and you show that these insights can really change outcomes".

4.2.2 A deep desire to understand

A recurring mindset mentioned by interview participants was an authentic desire to understand, achieved or demonstrated through an inquisitive mindset and by asking questions that guide data analytics and decision making. As Participant A states "…it starts with somebody asking a question". This aligns strongly with the data-driven decision making framework defined in Section 2.41. where the starting point of data-driven decision making is as a problem statement or question aligned to business needs.

Participant B suggests that "you need someone in a senior management position who comes from a sort of a research or a data-driven approach background or paradigm about thinking about things". An authentic desire to understand can also be defined as a

question or hypothesis driven mindset, where senior decision makers lead or influence the activities (and focus) of technical team members (e.g., data scientists, analysts and researchers). This is something Barton and Court (2012) elude to in their research too. Emphasising this perspective further, Participant D states, "You need to ask the right question" and "You're not a data person per se, but you are asking the question which they need to bring to your attention to answer your question" and "asking those questions to say, okay, cool, what am I looking for from this data?" Participant F explains the process through which decision makers guide activity by asking questions and demonstrating a data-driven approach,

> "But the evaluation and the robust discussion around what follows post the initial results of the POC (proof of concept) or the pilots, that's really where the value is I think because once there's a stake in the ground, it gives the executives and exco kind of a very clear kind of, you know, thing to kind of look at and say, listen, what about this, what about that? Try this, try that. And then they will give kind of more specific feedback around what could be changed, to make it better. And the teams will then go off and do that stuff, and then come back with their findings thereafter".

An inquisitive and curious mindset about what data is telling and what it can tell or highlight and wanting to understand the mechanics behind those data points also drives the right questioning and focused analysis. Participant C explains, "there's an attribute that I think people need, and that's to be inquisitive" and decision makers truly need to want to "understand what the causal link is". Similarly, Participant A comments "you almost need to become a part of that number as well as a part of that metric. You've got to understand the background to it, you got to understand the process that's gone into it".

But not only inquisitive about the problem statement, but also about the processes adopted, the quality of data used, assumptions, etc. As Participant C mentions "you probably have to trust that they have used the right methodology and have right data inputs because rubbish in rubbish out, right?" while Participant D commented "So it all depends on the quality of the question you asked, and the quality of data and the trustworthiness of the data you have". Decision makers need to understand how to

interrogate data derived insights, through asking the right questions. Participant F explains the process at the organisation where he works as the head of actuarial "And so exco will look at it and ask some relevant questions, even about the process. Guys, what about this, do you not think this is a better way to kind of structure the process, you know they will ask those probing questions and get answers. And from there, there is a decision that gets made as to what to do next". Participant D similarly explains, "Then you say, ok cool show me results. Then obviously you then interrogate the results if the person ran it correctly".

Lastly, Participant B emphasises that decision makers also need to be open to new ideas or opinions for them to be truly interested in understanding, and trusting of, what the data may be saying "Having a leadership team that acknowledges the need to be data driven and is humble enough to get people or know their limitations enough that they you know will listen to the outside people".

4.2.3 A willingness to experiment

Associated with an authentic desire to understand is the mindset and behaviour of experimentation or testing for quick and frequent discovery. In fact, Ransbotham, Kiron, and Prentice (2015) suggest that senior decision makers experiment with small decisions first and then quickly evaluate those outcomes. As Participant B explains, "You've got to run some sort of trial, for example where you implement on a small scale and you have a sort of a counter factual group or control group and you show that these insights can really change outcomes" and "you know, these small sort of proof of concept ideas where you know you can run this and see whether there is any lift in terms of outcomes".

The concept of experimentation was directly and indirectly mentioned by interview participants and refers to the willingness and eagerness of decision makers to quickly learn what works and what does not. This approach appears to assist in reducing decision making risks, where, as mentioned earlier in this study, decision making is fundamentally about taking risks in the pursuit of improved competition or sustainability. Therefore, senior decision makers should be actively involved in reviewing outcomes from tests, experiments or pilots. As Participant F highlights,

> "…it's about actually just getting your facts together. Making sure that that what the problem that you are trying to solve is a real problem. Trying to get as many proof-points together to such that, the solution you are proposing solves the problem that you've identified"

Gathering data, or proof-points, from running tests and experiments makes it easier for senior decision makers to make decisions about different aspects of the organisation. As Participant F explains, "…companies not enjoying the ROI of the data investments thus far. Typically, that happens when there is no defined use case that speaks to illustrating proof points earlier on in the process". The idea of gathering data or proof to de-risk decision making and to learn quickly is also mentioned by McAfee and Brynjolfsson (2012) who suggest that senior decision makers need to embrace evidence-based decision making. Running multiple experiments to quickly collect such evidence is one approach that can achieve this. Conversely, Participant C highlights the importance of gathering evidence by illustrating the difficulty he witnessed in his clients who did not know what to do next "kind of had their heads in the sand…there was this like stuckness in mentality…there's so much dysfunctionality around them that they kind of, like, don't even know where to start".

The drive to experiment to quickly learn what works helps reduce decision making risk and helps in guiding individuals towards the next best step in research or in implementation. These experiments and the experts analysing the resulting data are a key component in the data-driven decision making process (see Section 2.4.1) where insights need to lead to decisions and then actions, and the outcomes then lead to new knowledge gained and new questioning.

In addition to wanting to test and test quickly, there also appears a need to be willing to try something until you find what works or does not. Participant C, who was referring to a situation where senior decision makers were exhibiting the opposite of data-driven leaders, mentions "they need to have like a problem-solving mindset" and "but I think the antidote would be more of a mindset of like, let me at least do what I can". Participant B highlights the importance of this process and the importance of leaders being open to allowing individuals to conduct such experimentation "they serve as an interface between

the technical stuff and the actual business, and they feel like they are supported, from you know, the top".

4.2.4 Continuous incremental learning

Related to the desire to understand and experiment is the mindset of continuous learning. It is important to note that the term continuous implies a sense of momentum and frequency. Participant B states,

> "But how do you kind of action that? You know there are lots of organisations that have learned lots of other things, but that just sits somewhere and doesn't permeate through the business, or you can't. You can't iterate on it".

Participant B suggests that organisations should aim to "become learning organisations" and describes this willingness to always be learning as "the types of people…these kinds of driven, never kind of satisfied, always looking for answers, type of people".

Continuously building onto new insights, in as short a time as possible, and asking the correct follow up questions appears to be critical and aligns to the data-driven decision making process and the idea that decision makers need to truly want to learn and understand through questioning and testing. As Participant B states, "We've experimented on that. We figured it out. Let's move on to something else and not taking that personally. Yeah, I think it's a very useful trick to have" and "it's also about building on these feedback loops". Participant E comments similarly with "ultimately it comes back to short feedback loops" while Participant A stresses the importance of maintaining momentum,

> "the speed is crucial on that because, whilst the question still exists in the head… it gives you the opportunity to build some momentum. Yeah, wait three weeks, your momentum is actually gone. There's been 10,000 other questions that have come up since then, and people have essentially forgotten that they asked you a question"

Participant E also refers to incremental learning by referring to completing work, learning and then moving on. He mentions an agile approach helps in achieving this "But then, you know, so I think agile has helped as well, not because of the way it's implemented with scrum or whatever, but the idea that you finish what you start." Participant F

mentions the importance of maintaining momentum in the right direction through the use of piloting as well as agile or lean mentalities. Participant F states,

> "other organizations which I have also seen do that successfully outside of [removed] is where they've…taken small use cases to their board…and said, listen, I don't need a lot of money… and they try to be very economical and very resourceful…They identify the low-hanging fruit…quick wins that you can illustrate in a use case that will then speak to whether this idea can work or not. And then they build on those things".

4.2.5 Customer service mindset

The topic or theme of using data to better understand target users and therefore, better serve them came up frequently. There seems to be two sub-themes with one speaking more to the end user or customer and their needs and behaviours, while the second speaks more to internal customers and the internal processes needed to be a more data-driven organisation. Across both themes, however, the underlying need to be empathetic is mentioned. Participant B commented "it said openness, sort of the empathy, the emotional intelligence" while Participant E states "But how did the tools focus without empathy and without understanding? How can you build great tools like…I mean, I'm assuming the guys at Autodesk or at Adobe, are great graphic designers themselves?".

Participant E uses the example of a company who uses data to predict what customers want without consulting them first before sending them their purchases "And we know you so well that you won't send them back. You can send them back if you want to, but you won't".

To improve customer understanding Participant B highlights the need for decision makers to guide organisations in better understanding the contexts of internal and external customers "You know, you've got to know the context well enough". To drive this customer focus within organisations Participant E recommends that decision makers think carefully about how team members are incentivised "You gonna get paid on how happy your new customer is, which is this guy, the marketing guy. How happy he is with your software that you're running for him". Participant F stresses, "And customer customer customer, that's like number one. It has to be focused on making things better

for them…I think once you have… those things in place and you have…buy-in from your top management, you're pretty much a foot away". Specifically mentioning internal customers, Participant E highlights a sub-theme to this section which is a self-service mindset. Participant E comments that to really serve your internal customer, apply a mindset of providing them with access to their own data and tools that allow them to function autonomously. Participant E states. "He wants to make tools, so that the tools can be used by the people who are closest to where they are going to use them" and "completely open access for everybody to the same data at the same time".

4.2.6 Data-driven decision making as everyone's responsibility

Interview respondents mentioned the need, and important role senior decision makers play, in ensuring organisation wide alignment around the definition of data-driven decision making and the organisation's data use strategy. Participant E emphasizes that this means "forcing everybody to get in the same room more than once a year" while Participant B states, referring to implementing processes for integration, "It's about understanding how these things can kind of scale and building on process rather than that people" and "more about the organization or the organizational change that one has to put in place to make it so".

A strong theme that came through was understanding the needs of each other and serving each other to achieve organisational objectives and not just a single business unit's responsibility. Participant B states "connect the dots and say these guys are doing this, and this part of the organization is doing that. Let's get them to talk to each other and help each other out" while Participant E explains,

> "same as the IT department is not supposed to do the marketing function, but they understand that if their department doesn't deliver a good email service or enough tools, you know, or support the infrastructure for the tools which will host these data sets, whatever, then the marketing department doesn't work and then we all suffer as a company because we don't sell".

More than half of the interview participants highlighted the important role that data management and IT management play in realising an organisation's data strategy and that the technical and managerial interplay between data and the people aspect of a data-driven

approach appears to be a difficult concept to understand. As Participant B states, "I think that blend between individual and data is very difficult to achieve" and referring to existing decision makers "they do not fully understand the kind of…architecture, both technical and organizational, that needs to be set up to become a data driven organization". Both Participant E and Participant B agree that the technology and data orientated components of businesses need to redefine their core objectives. Participant E states "because you're not optimizing for the performance of the code, we're optimizing for iteration of tests with our customers so we can see what sells" while Participant B states, "set up your infrastructure so that the data collection and the data architecture is for operations, but… even more importantly, it's for that strategic insight".

Participant F explains that you can have a strong data culture but all technology has an important role to facilitate this culture,

> "So, it's…these kinds of challenges that you... despite having an organization that has a strong data culture, you still have these challenges. I suppose you can definitely overcome them. But it is kind of, you know, the hurdle that one needs to cross especially when you're trying to scale the solutions that you've historically had and has worked for you for quite long".

Participant F refers to technical debt, which refers to technologies that no longer serve the needs of the business and need to be replaced with newer or more appropriate technologies. "…as you kind of build your organization out and move it forward, you also need to key out technical debt, which is basically old systems, old structures and that sort of thing" and

> "…as the organization gets bigger and bigger, … you have a very deliberate strategy, by your CIO or CEO to manage that debt, and then bring it down over time and make sure that it doesn't become a hindrance to the progression of the business".

It was stressed earlier in this section that senior decision makers have an important role to play in terms of hiring senior individuals who have the technical skills to manage data and the flow of information in a way that aligns to the organisations data use strategy. To achieve this, senior roles within the data technology domain must also understand the broader strategy and how that strategy is to be realised. Participant B suggests, "rather

than having a sort of a CIO, a traditional CIO you know,… rather have a Chief Insights Officer".

4.3 Unique interview findings

This section discusses two insights that were only mentioned by one participant, however, still worthwhile mentioning given their suggested importance.

4.3.1 Choosing the right metric to target

Participant C stressed the risk that can come from using data to try drive activity and performance. Based on his experience he notes "…I don't think it encourages as a data-driven culture when people have that experience that the data is being used against them instead of for them". While being target driven and using a real-time datapoint to achieve this can be effective, it does come with risks. Again, Participant C emphasises,

> "I think the visible lesson in this is to choose the right target…fortunately, that's a good example of like the right way. …choose the right metric, then choose the right target. Do you want to target sales, or do you want to target customer satisfaction, that would probably be influenced by you?"

The message is that the wrong mindset can almost demotivate people when trying to drive outcomes using data as a tool to drive compliance, accountability or performance management. Participant C ends with noting how stakeholders felt when data was used against them. He states, "they feel disempowered to actually use this information to act in a different way".

4.3.2 The politics of data; silos and empires

Participant E mentioned the challenge of politics within organisations which he experienced in more than one organisation that was trying to become more data-driven and stresses that senior decision makers play an important role in driving the message that a data-driven culture is about inclusion and everyone working towards one common gaol, as in Section 4.2.6 above. He states, "and the people at the top level need to be comfortable saying, yeah, less political games, more salary driven stuff and more sort of driven stuff" and "because of political infighting, it is in everybody's interest to keep each

part of [company name removed] separate. So, they will never unify the customer numbers, which has been a project when I was there five years ago".

Conclusion

The findings from interviews have now been presented. The overall impression from these findings is that there was unanimous consensus that leaders matter and that organisations, even those who appear to be data-driven, are struggling to achieve their desired outcomes. Even from such a small sample there was a sense that the ROI to date has been low. At the same time there also appears to be consensus on what decision makers should do to overcome these common barriers. The next chapter discusses the implications of these findings with reference to the overall objectives of this research.

5 DISCUSSION OF RESEARCH FINDINGS

Introduction

In this section we discuss the implications of the eight findings from the interviews.

5.1 Leaders as advocates and role-models for data use

Feedback from the interview participants regarding "leaders as data advocates" suggest that senior decision makers cannot simply rely on strategic plans or other documents to do the advocating that is necessary to ultimately change the way data is used in their respective organisations. Senior decision makers need to be proactive and intentional about fostering the right behaviours and understanding. As Participant D highlighted, the term "data-driven" might not mean the same thing to everyone, so leaders need to explicitly explain through clear communication what it means for their organisation and then emphasise the benefits of using data by referring to examples of how they have successfully used data in the past. This will also show that they actually do act on data-derived insights. These findings also suggest that senior decision makers who believe in the value of data and actively repeat the benefits of using data in decision making and who intentionally highlight or describe data use success stories are more likely to drive increased usage of data within their organisations, therefore, cultivating a data use culture which ensures a complete process from "problem statement" to "outcomes" and "new knowledge" as per Framework 1 in Section 2.4.1. It is also clear from this feedback that future benefits will not be realised if organisational leaders are investing in data related technologies and skills because "it's the flavour of the month".

5.2 A deep desire to understand

The findings suggest that leaders, through their questions, have direct control over what data is collected, analysed and subsequently acted on. Decision makers need to understand that if they want to guide technical team members (e.g., data engineers, analysts and data scientists) towards the most useful organisational needs, then they need to ask questions stemming from a deep desire to want to understand more. Asking questions, that data can potentially answer, is particularly important attribute for senior decision makers because they are responsible for defining and realising the organisations strategy. The

questions they ask guide investigations and, therefore, data-driven discovery towards what is important for the organisation.

Asking guiding questions and giving feedback is nothing new in the paradigm of management and leadership, however, the megatrends driving a new sub-paradigm of decision making, that is data-driven decision making, implies that decision makers now need to adapt this behaviour. The results here provide some guidance; decision makers need to ask questions about (i) what is driving the trends visible in the data?, (ii) what levers (e.g., incentives) do customers react to?, (iii) what data can support our internal staff?, (iv) how trustworthy is the underlying data?, and (v) how robust is the numerical technique/s used? Decision makers must ask these questions to ensure they can confidently act based on any data derived insight or insights.

Lastly, decision makers need to be open to new ideas or insights that may go against their prior assumptions and beliefs. This is important because being data-driven implies acting on data (insights) and not assumptions. Dismissing data derived insights may not set the right example for others in an organisation and may contribute to why organisations are not realising their data use strategies and associated investment returns.

5.3 A willingness to experiment

Findings from the interviews suggest that decision makers need to be open to quick experimentation. This mindset of quick experimentation assists in reducing decision making risk by providing factual proof points (data) from which decision makers, especially those new to a data-driven way of decision making, can base their decisions on. The interview findings also suggest that these experiments are not larger research experiments, but quick trials and pilots that aim to gather critical data is a quick but trustworthy way.

A willingness to experiment demonstrates to the broader organisation that a decision maker is interested in better understanding their customers and associated data and that they are open to new ideas and beliefs – two important aspects mentioned above.

Quick experimentation also supports the data-driven decision making process (see Figure 5, Section 2.4.1) in that is supports (i) the development of guiding questions, (ii) generates insights, (iii) generates outcomes, and (iv) creates new knowledge.

5.4 Continuous incremental learning

A number of the participants referred to learning feedback loops, iterative learning and knowledge management. This aligns to the data-driven decision making process in Section 2.4.1 where outcomes lead to new knowledge or wisdom which then drives new questions and research. The issue of momentum is of particular importance given the challenges organisations are highlighting with regards to long periods of not realising investment returns. Quick experimentation may assist in maintaining momentum with regards to data insights and subsequent actions. One can imagine that if done well such organisations will learn and understand more about their customers, industries and organisations than their competitors, thus improving their competitive advantage and sustainability – resulting in tangible and relatively earlier returns to their investments.

5.5 Customer service mindset

Interview participants emphasised the importance of focusing on internal and external customers. Internal customers are members of an organisation who may require or benefit from certain data when executing their work responsibilities while external customers are an organisation's exiting or potential clients. The argument here is that by focusing data insight efforts on customer desires or needs an organisation will be able to increase their returns on data investments. To achieve this interview respondents emphasised the need to be empathetic and inclusive to truly identify what will add value. Being an inclusive decision maker implies including customers throughout the data-driven decision making process, from defining the problem statement or objective to outcomes and generating new knowledge. One can argue too that when combined with quick experimentation and a desire to understand what achieves valuable outcomes that an organisation is more likely to realise benefits from their data-driven efforts, reduce ROI timeframes and learn from failures and successes.

5.6 Data-driven decision making as everyone's responsibility

The literature review in Section 2 and the opening insights shared in Section 4.1.1 above highlight the important role that leaders play in aligning all activities towards a common and clear strategy for using data to achieve organisational objectives. This, and the other behaviours mentioned in Section 4.2.1 through to Section 4.2.5 above, ensures that data-driven decisions flow through the entire decision making process, from *question* to *new knowledge* described in Section 2.4.1. Senior decision makers must, therefore, see data-driven decision making as something every business unit and employee needs to adopt rather than a project, option or process only relevant for selected individuals. To achieve this, senior decision makers and leaders need to drive integration and encourage inclusion so that everyone understands they are all accountable to the same organisational objectives.

This implies there is a need for a fundamental change in the way data management and the IT business unit is seen and understood to add value. Referring to the organisational structure framework presented in Section 2.4.1 this interplay implies being clear and intentional for how the Technology Dimension achieves the objectives of the Organisation Dimension. In fact, Coburn and Turner (2011) allude to the importance of IT serving the needs of the business by highlighting that an individual's access to data, regardless of their rank or urgency, is defined by the technological infrastructure deployed.

Wixom, Yen and Relich (2013) stress this issue too and highlight the importance IT technology as a key asset in deriving value from data. They highlight the importance of deploying the right technologies, managing data for faster analysis, ensuring IT and other technical staff are either business savvy or understand business needs and employing the right skills to adopting the latest technologies. Furthermore, Davenport, Barth and Bean (2012) state "Coming to terms with big data is prompting organizations to rethink their basic assumptions about the relationship between business and IT — and their respective roles". The evidence gathered in this research suggests that senior decision makers must ensure that those responsible for the management of IT and data also serve the needs of those responsible for experimentation, analysis and delivering self-service tools.

5.7 Choosing the right metric to target

The insight gathered from one of the participants highlights an opportunity and a warning. Rallying team members around a specific data point to drive focus and performance can assist in achieving organisation wide buy-in. However, incentives and long-term sustainability may be compromised if too much emphasis is placed on such narrow data points or if such data is used to punish, belittle or scold individuals.

5.8 The politics of data; silos and empires

The central take-away here is more of a warning than a mindset or behaviour that supports the use of data. If various individuals or teams refrain from sharing data or data derived insights then indeed organisations will struggle to realise any benefits from their data related investments. Access to data, especially customer and other sensitive data, can be used for internal political means or to protect one's relevance. This outcome would most certainly derail the data-driven decision making process and lead to unsatisfactory returns. Decision makers will need to know how to spot such behaviours and advocate for changes in data governance policies.

6 SUMMARY, CONCLUSIONS, LIMITATIONS, AND RECOMMENDATIONS

Introduction

As pointed out in chapter one, this paper sought to achieve two main outcomes. The first was to provide leaders and other senior decision makers of organisations an understanding of the mindsets and associated behaviours they need to possess, develop and practise in order to cultivate a data-driven decision making culture within their organisations and to realise the benefits of their broader data use strategies. The second objective of this paper was to bring data-use and big data research closer to the heart of business leadership and management, since most literature on data-driven decision making predominantly focuses on the technical conceptual components such as technical data management technologies and data analytics skills. Based on this understanding, the study is summarised as follows.

6.1 Summary

Making strategic decisions is a fundamental management activity of any organisation and always involves some level of uncertainty or risk. Three megatrends are influencing how strategic decisions are being made while at the same time significantly reducing risks. These are: (i) a rapid increase in the performance, affordability and accessibility of IT, (ii) a continuous improvement in the ability to store, process and analyse data, and (iii) exponential growth in the amount of data being collected from online activity and connected devices. These megatrends allow for more organisations to use data to enhance their decision making processes, otherwise referred to as data-driven decision making.

Adopting such a process has been shown to significantly improve the quality and speed of interactions between organisations and their staff, customers, competitors and suppliers, resulting in overall performance gains and improved competitiveness.

Given this opportunity to improve decision making, organisations across most industries are investing in data use strategies. However, only a small percentage of these organisations are achieving their desired outcomes. It appears that the critical challenges or constraints organisations are facing are mostly people related, and not technology,

financial or process related. Challenges include (i) clearly articulated strategies and plans by executives for how data will be used to achieve business objectives, (ii) vague definitions, understandings and expectations with respect to data-driven decision making across different roles and levels within organisations, (iii) difficulty in building an organisation-wide culture of data use, and (iv) a lack of skilled talent in the labour market. All these, and some other, challenges ultimately result in the unsuccessful adoption or application of technologies and processes aimed at deriving actionable insights from data, thus leading to disappointing or delayed returns on investments into these data strategies and interventions.

Existing research provides an understanding of the data-driven decision making process (see Section 2.4.1) and the components of a data-driven organisation (see Section 2.4.2). However, currently available research does not provide enough insight into the types of decision makers and leaders that are needed to (i) facilitate an effective data-driven decision making process from *questioning* through to *gaining new knowledge* and (ii) craft and implement clear strategies and organisational structures that ensure all organisational dimensions or business units work towards a coherent data use plan.

Based on interviews with six experienced professionals this research paper argues that senior decision makers and leaders need to adopt the following mindsets and associated behaviours to fully unlock the benefits of any investments made into data related technologies and skills. These are (i) decision makers need to be data advocates and role-models of data-driven decision making, continuously sharing success stories and highlighting the importance of data within each individuals' own context, (ii) decision makers must have or develop a deep desire to understand the levers or background mechanics of metrics by asking guiding questions and evaluating the robustness of findings, (iii) decision makers need to be open to running small and fast experiments to gather proof points that aid in more informed decision making, (iv) decision makers need to maintain a level of momentum in learning and questioning by building on what is learnt from running experiments or mining data so that there is a continuous loop of feedback and learning, (v) decision makers must place a high level of importance on using data to understand and serve both external and internal customers by facilitating empathy and communication between all business units and customers, and (vi) decision makers need to ensure all business units, especially traditional IT and data functions, understand the

how to redefine and enhance their responsibilities towards the broader organisation's strategy for adopting a data-driven decision making approach.

Decision makers should also be aware of political infighting and the risks associated with unintended consequences of using data to influence employee behaviours.

6.2 Conclusions

Adopting positive and supportive mindsets and behaviours will help decision makers overcome many of the challenges their organisations are currently facing with regards to cultivating a culture of data-driven decision making and ensuring all business units work towards realising the organisations strategic objectives. It is clear from the data-driven decision making process outlined in Section 2.4.1 (Figure 5) that the process requires (i) multiple decisions to be made along the process from the *problem statement* to *new knowledge creation*, (ii) input from multiple team members and their respective skills, (iii) alignment in terms of process and expectations, (iv) access to relevant data technologies, and (v) alignment with the organisation's strategic plans. It is, therefore, clear that senior managers, business leaders and other decision makers have an important role to play in ensuring the ideal skills and technologies exist and that the ideal activities and discussions take place to overcome any *people* related issues that may result in bottlenecks or inertia regarding the data-driven decision making process.

Senior decision makers must understand and realise that their beliefs, mindsets and associated behaviours have a direct and material impact on how others behave and adopt data, what they focus on and how they structure themselves to facilitate organisation wide data-driven decision making. Leaders of organisations implementing data culture transformation projects must understand the data-driven decision making process and the important role each of the three organisational dimensions play in ensuring reliable data transforms into impactful outcomes and learning. A good example was presented by Participant F where senior decision makers based almost all of their decisions on data, encouraged quick experimentation, were open to new ideas and failure and ensured everyone in the organisation understood how they use data to compete in their industry and markets.

Senior decision makers, and more importantly, any contracted practitioners, must understand that data transformation projects must consider and address the mindsets and behaviours of senior decision makers as much as they focus on the technological and technical skills components of their interventions, otherwise organisations will continue to struggle to effectively transform data collected into actionable and impactful insights.

6.3 Recommendations

The following measures are suggested to address the *people* related challenges hindering effective data-driven decision making in organisations investing in data related technologies and skills:

Operate as advocates and role-models for using data in decision making

Priority number one is to end silos mentality by making data use a shared responsibility among individuals and teams. This needs to be communicated through the behaviours of senior decision makers, institutional policies and organisational communications so that all members of the organisation know what is expected of them. People in the organisation must understand and buy-in to the organisation's data strategy and understand how it will stimulate growth and ensure long-term sustainability of the organisation.

Have a deep desire to understand what the data is saying and what it does not

Senior decision makers need to guide the activities of members by asking genuine probing questions that ensure continuous progress towards positive actions and outcomes is maintained. An authentic desire to understand (i) what is driving the trends visible in the data?, (ii) what levers (e.g., incentives) do customers react to?, (iii) what data can support our internal staff?, (iv) how trustworthy is the underlying data?, and (v) how robust is the numerical technique/s used?, are suggested starting points.

Are open and eager to implement experiments or pilots to gain new insights

Leaders and other senior decision makers are encouraged to promote the use of quick experiments or pilots to rapidly generate fact-based data-driven insights that reduce decision making risks. Decision makers need to be open to new ideas and trends (resulting

from these experiments) that may contradict their current assumptions and beliefs. Rapid experimentation also ensures continuous momentum and progress with regards to the data-driven decision making process.

Be life-long learners

Employees in both professional and unskilled occupational categories should be given proper training and induction on how to identify, document and utilise data in their respective roles. Some individuals may assume that because they are not data engineers or analysts that they are not included or responsible for ensuring a data driven culture is cultivated. As discussed above, and illustrated in the data-driven decision making framework (Figure 5), the process of using data to address a business need or realise a business strategy involves all members, from technical data experts to HR, sales, general management, research and development, etc. With regards to training, first priority should be given to team leaders and supervisors, as well as HR teams as they interact directly with lower level employees on a daily basis and content should cover both the technical aspects as well as the *people* aspects discussed in this research.

Focus data and broader strategies towards servicing internal and external customers

It is imperative that decision-makers use data to improve (internal and external) customer responsiveness rather than focusing on routine operational issues alone. By focusing on direct customer needs is one way of ensuring data activities work towards positive returns to the organisation.

Ensure all members understand how they (and technology) support the organisations data-driven decision making process

Across teams, there needs to be a common understanding of what the organisation's data strategy is, how a data-driven approach results in improved competitiveness, why it is required and how it can be used strategically. This requires a culture of open communication and dialogue between management and employees at all levels.

Identify and select appropriate data points for assessing performance

Ideally, data use should be monitored regularly to ensure that it yields the desired outcomes in all departments. Useful monitoring tools include dashboards, report backs by cross-functional teams; project steering committee meetings; information sharing sessions; and oral presentations by team leaders on how they experience data use in their units and organisation-wide surveys to get a sense of how people in the organisation feel about the use of big data in their routine jobs.

Ensure politics, silos or empire mentalities do not form based on access to data

Senior managers and leaders must ensure they know what data silos or data empires look like and be able to "break them down" so that all members are able to safely access data and insights necessary for the efficient flow from data to outcomes within their respective business units.

6.4 Limitations of the study

It is worth mentioning some key limitations of this study. Firstly, this study does not explore how to develop or practise any of the skills, knowledge, mindsets or behaviours mentioned. Secondly, the degree of mastery or the degree of importance of mindsets and behaviours identified is not investigated. Lastly, this research paper does not prove or claim to prove that the mindsets or behaviours identified are indeed critical or the only mindsets required for overcoming the common data use challenges identified. The author recommends future researchers to use a larger sample size of interview participants and to identify case studies where changes in senior management resulted in positive changes to an organisation's data use culture or processes.

6.5 Future research

This research provides leaders and other senior decision makers of organisations an understanding of the mindsets and associated behaviours they need to possess, develop and practise in order to cultivate a data-driven decision making culture within their organisations and to realise the benefits of their broader data use strategies. These mindsets and behaviours will also assist in overcoming the common *people* related barriers most organisations are facing. This research also brings data-use and big data research closer to the heart of business leadership and management, since most literature on data-

driven decision making predominantly focuses on the technical conceptual components such as technical data management technologies and data analytics skills.

Future research should focus on confirming these findings, for example, does running smaller experiments really lead to more data driven decision making, and if so, why?. Future research should also be conducted in different contexts, such as specific industries or different locations. Future research should also aim to address some of the weaknesses of this research paper by (i) interviewing a larger and more diverse sample of participants from different genders, geographies and industries, (ii) include a portion of structured interview questions to allow for some tests of similarity and perhaps ranking of feedback across interview participants, and (iii) include case study research that discusses successful and unsuccessful data transformation projects. Adopting these recommendations will also help in better understanding the psychological mechanisms between mindsets and behaviours and how these target mindsets can be developed within existing leaders.

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APPENDICES

Appendix 1.1: Data collection instrument(s)

Below is a copy of the semi-structure interview guide used to facilitate interviews.

Interview guide - A qualitative investigation into the behaviours and mindsets necessary for cultivating and leading a data-driven organisation

Introductions (5min)

- Appreciation and thanks
- Names and backgrounds

Consent and other formalities (5min)

- Repeat confidentiality issues
- Request for interview conversation to be digitally recorded for transcribing purposes
- Data storage and destruction processes

Research background and purpose statements (10min)

- Do you understand the research and its objectives?
- What questions, thoughts or concerns do you have regarding the research?
- Do you agree with the following statement "there are some leaders who are more suited to leading data-driven interventions or organisations because of their beliefs, mindsets and perspectives"?
- Why do you agree or disagree?
- Can you recall working with someone who typified/personified what a data-driven leader means to you? Explain further…
- Do you believe you are data-driven? Why or why not?
- What has been your experience in leading or executing work in this regard?
- Are you an expert in this work? Or can you recall working with an expert?
- Briefly describe the key objectives of this component of a data-driven organisation in your own words based on your own experience.

Please take your time to visualise the type of leader that would epitomise / exemplify the perfect person for implementing and achieving a data-driven organisation.

- What attitudes do they have?
- What mindsets do they have?
- How do they approach the objectives?
- What do they believe in?
- How do they solve problems or how do they act and interact?

Appendix 2.1: One-page bio of the researcher including declaration of interest in the research and funders, if any

Jef Jacobs has experience in Project management, business development, strategy and innovation and currently works at an NGO called New Leaders Foundation. He has over 6 years of experience working on the DDD Programme and 5 years as a management consultant at Monitor Deloitte. He also has extensive knowledge and experience in education, analytics, economics, strategy and innovation. He is currently involved in a large data transformation programme aimed at embedding data-driven decision making within schools and education districts in South Africa.

Academic history:

- Wits University: Bachelor of Economic Science
- Wits University: Honours, Bachelor of Economic Science
- Wits University: Masters, Bachelor of Economic Science
- Wits Business Schools: MBA candidate.

Employment history:

- NLF: DDD Programme manager: 2019 – Present
- NLF: DDD Analytics & Insights manager: 2015 – 2019
- Monitor Deloitte: Manager in Strategy & Innovation: 2014 – 2015
- Monitor Deloitte: Senior Consultant in Strategy & Innovation: 2012 – 2014
- Monitor Deloitte: Consultant in Strategy & Innovation: 2011 – 2012
- Wits University: Associate lecturer in economics: 2009 – 2011

I Jef Andreas Jacobs declare that this research report entitled 'A qualitative investigation of the mindsets and behaviours that are necessary for cultivating data-driven decision making within organisations' is my own unaided work. I have acknowledged, attributed, and referenced all ideas sourced elsewhere. I am hereby submitting it in partial fulfilment of the requirements of the degree of Master of Business Administration at the University of the Witwatersrand, Johannesburg. I have not submitted this report before for any other degree or examination to any other institution.

My current employer, New Leaders Foundation has partly funded my MBA as part of the foundation's employee skills development plan.

Appendix 2.1: Ethic documentation

All ethics documentation has been provided to Wits University in submission of this research paper.

Appendix 3.1: Dully filled in data collection instrument(s)

Transcripts of each of the six interviews are available on request and have been shared with my research supervisor.