Exploring the role data-driven decision-making under uncertainty

Munyaradzi James Hove

19384289

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Abstract

Decision making requires managers to carefully analyse the business environment and make sense of existing information in a bid to direct and influence particular courses of action for organisations. However, there is complexity of this process in uncertainty, such as that exemplified by the year 2020 due to the effects of the global COVID-19 pandemic. Within this context of uncertainty, and given the proliferation of big data, the role of data-driven decision-making under uncertainty is yet to be established.

This research explored the role of data-driven decision-making under uncertainty, including the preconditions for, enablers and functional benefits thereof. This research was a qualitative study through 10 in-depth interviews with South African senior managers, who made use of data to support their decision-making processes. The understanding of the role of data-driven decision-making was explored using thematic analysis.

The researcher presents an integrated model of the data-driven decision-making process under uncertainty, that can be adopted by organisations and decision-makers faced with uncertainty, in need of improved rationality, enhanced objectivity and more accurate probability modelling under uncertainty. This integrated model outlines key preconditions for data-driven decisioning under uncertainty and the challenges categorised as organisation specific, external to the organisation, inherent to the data and data management practices. The integrated model also outlines key enablers for data-driven decisioning under uncertainty as well as the perceived benefits, pivoting between strategic and application benefits.

Keywords

Uncertainty, Complexity, Data-Driven Decision-Making

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Munyaradzi James Hove
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1. Introduction

This chapter provides an introductory overview and background to this study, which investigates data-driven decision-making under uncertainty. The discussion begins with background context on the research through which the research problem is introduced. The theoretical and business significance of the research as well as the scope and purpose of the research are also explained.

1.1. Background to the Research Problem

The past decade was characterised by the rapid emergence of what is termed ‘big data’ (BD). Companies across various industries are still exploring this emergence with a view of exploiting it for competitive advantage. As such, big data is a key component of data-driven decision-making processes of any organization; ultimately aimed at improving decision-making quality. Despite the vast amounts of data and data sources available, there are still challenges aligning these with decision-making within firms (Provost & Fawcett, 2013). According to Horita, Albuquerque, Marchezini and Mendiondo (2017), the proliferation of smart devices has accelerated access to new data sources, adding to the already complex webs of data. However, this data is yet to be effectively harnessed to support decision-making because it fails to reach the decision makers in a suitable way (Horita et al., 2017)

According to Corbett (2017), big data is not necessarily only ‘big’ in size. Rather, it is different from traditional data in terms of the ‘4Vs’ of volume, variety, velocity, and veracity (Goes, 2014). The value of big data is found in the ability to exploit various combinations of these 4Vs (Goes, 2014). This is corroborated by Ghasemaghaei and Calic (2019) who describe a survey that showed that 25% of firms reported that processing and analysing big data via their big data investments had started to yield positive results.

The declaration of the SARS-Cov-2 (Coronavirus), a novel virus that causes the disease COVID-19, a global pandemic (WHO, 2020), resulted in unprecedented global turbulence. For business, this created conditions that were described as volatile, complex, uncertain and ambiguous (VUCA). For instance, during the month of April 2020, crude oil futures crashed to historic lows (Trading Economics, 2020). Economists attributed this crash to reduced mobility that followed widespread implementation of national emergency measures to reduce the spread of the virus, disrupting delivery of oil on maturity dates (Offshore Technology, 2020). This event highlights the complexity of the environment within which decision-makers found themselves. In response, the Chinese government was able to leverage emerging technologies such as big data and artificial intelligence demonstrating significant benefits of adopting data-driven decision-making strategies (World Economic Forum, 2020).

Evidently, technology and data can be employed for making decisions at a macro and national level in times of crisis. These experiences have spurred interest in the *role of data-driven decision-making and how it can be optimised in organisations confronted with uncertainty*.

1.2. Research Problem

In South Africa, the COVID-19 pandemic led to corporates being financially distressed, resulting in corporates such as Edcon and Comair filing for business rescue (Business Tech, 2020). It was projected that the effects of the pandemic would be far reaching across all industries as firms, not classified as essential services, were forced to close for an extended period.

It is in such periods of uncertainty, that decision-making and continued alignment of the components of strategy becomes vital for survival as well as creation and protection of competitive advantage (Trahms, Ndofor & Sirmon, 2013). Uncertainty refers to an environment that renders a decision maker unable to forecast the outcomes of the future due to inadequate access to information required to guide decisions (Bîlcan, Ghibanu, Bratu & Bîlcan, 2019). A different view describes uncertainty as characterised by volatility and disturbance of economic agents, being most financial measures, that renders them difficult to forecast (Jurado, Ludvigson & Ng, 2015)

As the operating environments for businesses become increasingly volatile, uncertain, complex and ambiguous, this requires decision capabilities to keep businesses on course (Horney, Pasmore & O'Shea, 2010). The need for speed in decision-making and execution requires tools and techniques that can meet this need. The COVID-19 pandemic and responses thereto by economies around the world, have resulted in increasing uncertainty for the future. As a result, there is significant pressure on managers to make effective decisions that ensure business success (Maitland & Sammartino, 2015).

According to Rejikumar, Asokan, Sreedharan (2020, p. 279) data-driven decision-making (DDDM) refers to "the approaches business firms, and managers are adopting in decision-making on the strength of verifiable data". Uncertainty on the other hand, refers to a situation where there is "incomplete information that does not allow a complete list of the consequences of a decision to be formulated" (Bîlcan, Ghibanu, Bratu & Bîlcan, 2019, p. 126). Big data analytics capabilities are defined as the ability of the firm to capture and analyse data, input for the generation of insights (Gupta & George, 2016). A concise big data analytics strategy provides direction for the firm and stakeholders with respect to the objectives and approach to big data analytics initiatives. However, it remains unclear what conditions need to be prevalent, if at all, for such technologies to lead to competitive gains (Mikalef, Krogstie, Pappas & Pavlou, 2020).

1.3. Significance of the Research

This section provides a description of the significance and relevance of this study from the perspective of the business as well as theoretical need.

1.3.1. Business Need

A 2018 survey captured data from ***senior managers*** in 57 large corporations, showed that companies continue to believe they are getting value from their big data and artificial intelligence projects (Davenport & Bean, 2018). Furthermore, the results of this survey showed that 73% of respondents stated that they had already received measurable value from these initiatives. In addition, compared to the 2017 number, there was notable growth year-on-year which suggests that more value was realised as companies grew more familiar with emerging technologies (Davenport & Bean, 2018).

These findings align with earlier work (Ransbotham, Kiron & Prentice, 2015) which indicated that organisations had a higher probability of generating competitive advantage by combining analytical skills and business knowledge. This combination is the goal targeted by data-driven decision making.

However, despite all of this theoretical knowledge, a report from the Companies and Intellectual Property Commission (CIPC) of South Africa revealed that over 100 companies filed for voluntary business rescue as a result of a national lockdown period implemented in March 2020 (Money Web, 2020). Notable examples were Edcon, a large clothing retailer; a local airline, Comair; and Phumelela Gaming and Leisure, a horse racing company; large firms that succumbed to the uncertain business conditions instigated by the COVID-19 pandemic. Whilst the very nature of business rescue is to mitigate the impact of insolvency risk, statistics show that a total of 2042 companies were liquidated by the end of 2019, an increase of 11% from the 2018 figure. Of these 258 were compulsory interventions and the balance of 1784 voluntarily initiated (Stats SA, 2020a).

Whilst economists advised that South Africa slipped into economic recession in 2019, after contracting by 1.4% in the fourth quarter (Stats SA, 2020b), the above statistics show underlying weakness in decision making competency in organisations during times of uncertainty. Given the backdrop of economic contraction in 2019, the devasting effects of COVID-19 on the economy may be far worse in their impact. Therefore, this research set out to explore the role of data-driven decision-making as a means to not only gain and protect competitive advantage and market share but also identify ways to alleviate dire adverse effects of uncertainty on businesses.

1.3.2. Theoretical Need

Brynjolfsson and McElheran (2016a) conducted a study using data collected by the U.S. Census Bureau for the years 2005 to 2010. They found that manufacturing firms in the United States that adopted data-driven decision-making experienced improved performance and productivity (Brynjolfsson & McElheran, 2016a). It is, however, unclear, what role data-driven decision-making had in the year 2008, which was characterised by the global financial crisis (Mukunda, 2018). It can be argued that this, and subsequent years post, was a period characterised by uncertainty as evidenced by the stock market crashes (Bloom, 2014). Well researched and documented decision-making techniques under uncertainty include heuristics. Their popularity is largely owing to the speed of decision-making these techniques provide a decision-maker (Artinger, Petersen, Gigerenzer, & Weibler, 2014). However, the inherent challenge of heuristics is the biases that the decision maker is exposed to, that may lead to decision errors (Dietrich, 2010). Following on this premise, Einhorn (2020) advocates for strategic decision-making process requires a decision maker to be aware of their biases and use data to make decisions systematically and analytically under uncertainty. McCann (2020), one of the major challenges of uncertainty is the rationality of the decision-maker.

Given the above theoretical insights from current discourse and critically analysing the Brynjolfsson and McElheran (2016a) study; there is an apparent lack of clarity on the role, preconditions and enablers, as well as the resultant benefits of data-driven decision-making under uncertainty. This has, therefore, poised itself as a research gap for the researcher and motivated for this study.

1.4. Research purpose

Given the business and theoretical need for this research, a primary objective of this study was, therefore, to explore and understand the *role of data-driven decision-making under uncertainty*. The sub-objectives of this study were to:

- Understand the level of knowledge, perception and attitudes of South African senior managers' towards data-driven decision-making under uncertainty;
- Explore the ways in which South African senior managers use big data to make decisions under uncertainty;
- Identify the challenges South African senior managers encounter when using big data to make decisions;
- Solicit guidance on what is required to enhance the use of data-driven decision-making under uncertainty in organisations; and
- Understand the impact, (advantages and disadvantages) of data-driven decision-making during periods of uncertainty.

1.5. Conclusion

Having pursued insight in service to the objectives for this research as set out above, the researcher makes practical recommendations to business regarding the application of data-driven decision making under uncertainty. These are documented in Chapter 7 of this research. The chapter also details how the empirical outcomes positively contribute to scholarly understanding of data-driven decision making.

2. Literature Review

The preceding chapter introduced background context to the research problem and justified the business and theoretical need for this study. This chapter presents related arguments and concepts that indicate the scholarly debates with which the study aligns. In so doing, a basis for new theoretical contribution is detailed and its relevance substantiated.

The discussion begins by setting context on uncertainty, big data and big data analytics capabilities as phenomena. The link with data-driven decision making and decision making in uncertainty is then expounded, bringing forth insights of the Fourth Industrial Revolution and other aspects of data.

2.1. Uncertainty

Risk is a phenomenon in which the probability of an outcome or occurrence is known. In contrast, uncertainty is explained as a decision scenario in which the information available is insufficient for conclusive indication of what a specific decision will yield (Bîlcan, Ghibanu, Bratu & Bîlcan, 2019). In light of the unknown outcomes and consequences, decision-making in uncertainty is often aimed at mitigating risk that this poses to an organisation. A similar view of uncertainty states that for a decision maker, the distinct aspect of its nature lies in the inability to know outcomes and consequences, as well as determining the probability thereof (Kokinov & Raeva (2006); Mousavi & Gigerenzer (2014); Pleskac & Hertwig (2014). Further corroboration from Maitland and Sammartino (2015), characterizes the insufficiency of information or lack thereof as a key indicator of uncertainty.

Economics Professor Nicholas Bloom asserts that uncertainty as a concept cannot be clearly defined. This is because uncertainty varies across countries, largely dependent on the stage of economic development with emerging and low-income economies found to experience higher uncertainty (Bloom, 2014). The primary distinction between uncertain versus certain environments is simplified as scenarios of unknown unknowns and known knowns respectively (Gigerenzer & Gaissmaier, 2011; Baltussen, van Bekkum & van der Grient, 2018). If there is certainty about the nature of the environment in the future, solutions to challenges are readily available.

Whereas, if the environment is uncertain, bounded rationality in decision making is inapplicable (Gigerenzer & Gaissmaier, 2011). Another view is that of Jurado, Ludvigson and Ng (2015, p. 1177), who define uncertainty to be “the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents”. Economic agents in this context are inferred to be economic gains of organisations in terms of operating profits, capital gains, balance sheet solvency and liquidity. The difficulty in forecasting these economic agents can be attributed to the insufficiency of information.

According to Horney et al. (2010), innovation and changes in macroeconomic levers such as people, process and technology have led to the emergence of environments that are volatile, uncertain, complex and ambiguous (VUCA). Millar, Groth and Mahon (2018), identified disruptive innovation as a driver of and outcome of uncertainty. According to Artinger, Petersen, Gigerenzer and Weibler (2014), the introduction of new products and services have also been identified as drivers of uncertainty.

Bad events like oil-price shocks, terrorist attacks and wars often seem to increase uncertainty, and this uncertainty is commonly measured by the volatility of the stock markets and in some cases, GDP (Bloom, 2014). To exemplify this phenomenon, one of the characteristics of uncertainty that was prevalent during the period of COVID-19 pandemic was stock-market volatility as supported by literature (Altig, Baker, Barrero, Bloom, Bunn, Chen, Davis, Leather, Meyer, Mihaylov, Mizen, Parker, Renault, Smietanka & Thwaites, 2020). Furthermore, South Africa’s real GDP decreased by a record 51% in the second quarter of 2020 owing to the impact of the COVID-19 lockdown restrictions implemented at the end of March 2020 (Stats SA, 2020c).

In Europe, Italy was one of the countries that was significantly affected by the COVID-19 pandemic recording a fatality rate of 7.7% by mid-March 2020. This led to an observation by Lazzerini and Putoto (2020, p. 641), that “clearly, better data are needed to support decision making and to build public awareness”. This underscores the notion that decision-making under uncertainty is extremely complex, due to the decision maker not being aware of the existence or extent of a problem due to inadequate quantitative and qualitative information that may be relevant (Bîlcan et al., 2019). Given the above, it is increasingly apparent that big data and big data analytics can address the sufficiency of information for quality decision making under uncertainty.

2.2. Decision-making in uncertainty

When complexity and uncertainty grip the business environment, organisations need to be agile (Horney et al., 2010). Agility allows for organisational flexibility, speed of execution and anticipation of problems that allow for timely responsiveness to the impact of uncertainty. Daly (2016) emphasizes the importance of managers being able to continually respond and adapt to the changes in the decision environment. Furthermore, Mousavi and Gigerenzer (2014, p. 1672) express the need for “simple robust solutions” in a complex and uncertain environment. This has typically led to the emergence of decisions reliant on heuristics (Artinger et al., 2014; Mousavi & Gigerenzer, 2014), being simple rules of thumb applied to navigate complex and uncertain environments.

According to Daly (2016), the different decision types require different types of information and as a result, data analytics and data analytic capabilities of an organisation play an integral role into the decision-making quality and effectiveness. The study points out that managers employ a number of strategies to navigate uncertainty in their decision environment. These include (1) delaying decisioning to source more information; (2) assessment of the existing uncertainty context; (3) cognitive application to the problem and solution; and (4) decisioning, with a feedback loop to information tools for future decisions.

In *delaying decisioning*, the decision-maker attempts to structure the uncertainty and complexity of the decision by creating sub-decisions and proforma steps to break down the decision problem to simpler, more comprehensible clusters. According to Daly (2016), an *assessment of context of uncertainty* is required, as often, uncertainty presents different ways, requiring different decision types to navigate the uncertainty. *Cognitive application* to the problem and solution, is an in-depth analysis and definition of the problem, to which solutions for that problem can be formulated. The last step is the actual decision-making, to which a *feedback loop* necessitates future decisions and process. An extract of the model linking management decision-making and the information required is shown in Figure 1 below. This model has been adapted to show the decision problem focus, problem solution constraints, the decision makers and information requirements. Specific to a South African context, mirrored with the study by Davenport and Bean (2018), senior managers appear to be the ones tasked with the execution of the strategy of the business and the figure below is practical to the decisions they are faced with making under uncertainty.

<table>
<tr><th colspan="2">Decision Making</th><th>Information Demand</th><th colspan="2">Information Supply</th></tr>
<tr><th>Decision Problem Focus</th><th>Problem Solution Constraints</th><th>Information Required</th><th>DSS</th><th>People</th></tr>
<tr><td>Future Organisational Strategy</td><td>External Environment</td><td>Often beyond language: fused view of external industry information and internal status quo</td><td>Intuituve conceptual modelling possibilties</td><td rowspan="2">Executive & Senior Management</td></tr>
<tr><td>Policy Type Decisions</td><td>Ambuity because of complex and uncertain external environment</td><td>BI & Big Data Analytics for customer profiling and validation of external signals</td><td>Modelling tools that would generate solution scenarios</td></tr>
</table>

Figure 1: Decision Making, Information Demand and Supply

Source: Adapted from Daly (2016)

A similar view of this approach to data-driven decision-making under uncertainty, is that of Einhorn (2020), who suggests a four-step process when decisioning in uncertainty. In her article, she suggests that decision-makers ought to (1) identify the category of historical data they are working with; (2) recognize the cognitive biases triggered by each category; (3) invert the problem to identify what is required; and then (4) formulate the right questions for the answers required. The above suggests that decision-making under uncertainty and the quality of decisions hinges primary on the use of data to further analyse a problem or decision-point ***rationally***. In the four-step process by Einhorn (2020), the historical data on which decisions are based is grouped into three main categories, which are *salient, contextual and patterned data.* Accordingly, the biases these data trigger are the *salient bias*, which is a bias that cause a decision-maker to place greater emphasis on new information resulting in planning errors and poor decision quality. Contextual data is said to cause a *framing bias,* triggered by the context in which the data is delivered. The one example in which this bias emerges, is in the context of a marketing strategy adopted to alter the price of a product from “R3.02” to “R2.99”. The decision maker is encapsulated in context that creates a bias to lead the decision maker to believe that R2.99 is significantly cheaper than R3.02. Lastly, patterned data is suggested to cause a *clustering illusion*, whereby a decision-maker begins to assume events and outcomes follow a specific pattern (Einhorn, 2020).

The need for rational decision-making under uncertainty is motivated by one of the impacts of uncertainty, being the inability to predict the consequences of decision outcomes. Therefore, no set of responses are equipped to plug into any situation but rather, decision options are analysed and applied to fit a specific decision case (Mousavi & Gigerenzer, 2014). Following the same logic, a poor-quality decision taken under uncertainty, without exhausting all possible data and insights drawn from the data could be costly to the organisation and logically so, a well-executed data-driven decision could be giving the organisation a competitive edge.

The business environment is subject to constant changes as organisations fiercely fight for market share and competitive advantage. These changes occur in both the macro and microenvironments, with the levers being technology, competitors and the consumer (Artinger et al., 2014). It is argued that broad-based consolidation of competitor and consumer information resulted in the emergence of big data, ultimately leading to data-driven decision-making (DDDM), which is the use of data in the decision-making process which is aimed at reducing the risk and impact of uncertainty (Brynjolfsson & McElheran, 2016a). Ransbotham, Kiron and Prentice (2016) highlight the value of using of data in decision-making as a means to aid assessment of consequences and probabilities of decisions. Older, yet relevant literature exists that guides decision-makers on how to cope with uncertainty. For example, Lipshitz and Strauss (1997), describe RQP heuristic as one of the standard procedures for coping with uncertainty.

Similar to Daly (2016) and Einhorn (2020), the Lipshitz (1997) RQP heuristic set the tone for decision-making under uncertainty, proving applicable in formal and behavioural decision theories. The RQP heuristic explains the process of *reducing* uncertainty by performing a thorough and rigorous information search to *quantify* the uncertainty that cannot be reduced and then *plug* this uncertainty with a carefully designed course of action. Lipshitz and Strauss (1997) further express the reduction of uncertainty as being tactical in nature, heavily reliant on data to support the decision-making process to build different scenarios that could possibly play out.

2.3. Leadership to address uncertainty

The preceding sections have established uncertainty and decision-making in uncertainty. Given that, it is imperative to analyse and understand the costs of uncertainty and what is expected of leadership during these times. According to King and Badham (2019), uncertainty has a financial impact on organisations, and this is driven by mental health and its effect on employee performance. Stress is reported to cost the United States up to US$225.8 billion annually in lost productivity owing to absenteeism.

The high cost of uncertainty calls upon exceptional leadership to address this uncertainty. According to King and Badham (2019), to enable and encourage performance in VUCA environments, leaders need to possess attributes such as systems thinking, tolerance of ambiguity and a learning mindset. An earlier view is that of Uhl-Bien and Arena (2017), who argue for Complexity Leadership. This type of leadership is aimed at enabling employees and organisations for adaptability. Uhl-Bien and Arena (2017) introduce emergence, which is explained as the combination of resources such as people, technology and information interacting in a system, resulting in the creation of something new that did not exist before. The resources are referred to as agents and the systematic interaction is a network. Uhl-Bien and Arena (2019) explain that a new order brings about complexity and "it will take complexity to beat complexity" (Uhl-Bien & Arena, 2019, p. 10).

Therefore, the appropriate response to the emergence, being the creation of a new order; something that did not exist and does not fit the criteria of what is known i.e., complexity, is to be **adaptive**. The leadership required for complexity requires three types of leadership for adaptability: operational, entrepreneurial and enabling leadership (Uhl-Bien & Arena, 2019). This leadership approach is quite similar to King and Badham (2017) in that they also allude to systems thinking and a leaning mindset. Such a mindset sets a premise for what the term the *Mindfulness Revolution*. The key take outs of the *Mindfulness Revolution* are **"knowing that"** which focuses on the nature of individual and organisation, as well as **"knowing how"** encompassing the capabilities of awareness, attention and acceptance (King & Badham, 2017, p. 13) which blends well with the adaptability advocated for by Uhl-Bien and Arena (2019).

2.4. Data-driven decision-making

According to Rejikumar, Asokan, Sreedharan (2020, p. 279) data-driven decision-making (DDDM) refers to “the approaches business firms, and managers are adopting in decision-making on the strength of verifiable data”. In an earlier study by Brynjolfsson & McElheran (2016a), data-driven decision-making is defined as the adoption and use of data to support the decision-making process of an organisation. This approach to decision-making came about as a result of the perception that management was an art as opposed to a science, which had rendered managers complacent by being comfortable making decisions intuitively (Rejikumar et. al, 2020).

Janssen, van der Voort and Wahyudi (2017) point to the quality of big data as a factor influencing data-driven decision-making. However, there remains inconsistency in the definition of data quality (Günther, Colangelo, Wiendahl and Bauer, 2019). Rather, common dimensions namely (1) consistency; (2) completeness; (3) accuracy; (4) timeliness; and (5) relevancy have been identified. In another study, made more practical by using data from the internet, Sun, Dawande, Janakiraman and Mookerjee (2019) establish the importance of the “traffic [data] quality”. In their study, the quality of traffic [data] was in relation to Google AdSense that analysed the number of “clicks” and moderated this using the clever algorithmic analysis of the user’s intent to establish the conversion probability; that is the probability that a click led to a sale. Janssen et al. (2017) note that data quality is not the sole factor for data-driven decision making and that other factors such as the ability to collect, prepare and analyse data, requires sound decision maker quality. The abovementioned characteristics are collectively known as big data analytic capabilities (Janssen et al., 2017).

Given what we know about uncertainty thus far, in particular, the inability to effectively and conclusively predict the outcome of a decision, McCann (2020) puts forward a compelling argument for data-driven decision making in uncertainty. He argues for Bayesian Updating as a “formal way of updating probability estimates in the light of new information” (McCann, 2020, p. 27). Under uncertainty, managers must still make decisions despite the insufficiency of information and with Bayesian Updating, new information is combined with existing or prior beliefs. The Bayesian Updating approach has been found to be an effective tool to assess and evaluate data aiding data-driven decision-making processes. This reduces cognitive biases whilst fostering open-mindedness and clarity of communication (McCann, 2020).

The Bayesian Updating approach to data-driven decision-making is one method of ensuring rationality of decisions under uncertainty. One of the effects of uncertainty is a potential breakdown in the decision-making process (Einhorn, 2020). In fact, the very awareness of uncertainty is the first step towards motivating rational [data-driven] decisions. This view is similar to Lipshitz et al. (1997), whose study argued for the acknowledgement of uncertainty as the second step to coping with uncertainty. According to Einhorn (2020), the first step is to analyse the data you are working with, be it (1) salient; (2) contextual; and/or (3) patterned data. The first three of the four steps explained in Chapter 2.2 above are all aimed at reducing cognitive biases and ultimately "promise to improve the quality of managerial decisions made under uncertainty" (McCann, 2020, p. 28).

It is, therefore, inferred that uncertainty has the unfortunate effect of compromising rationality of decision makers, which inadvertently results in the deterioration of the quality decisions made by mangers under uncertainty. It can, therefore, be concluded that data-driven decision-making, which is the use of data to support the decision-making process (Brynjolfsson et al., 2016a), has the valuable benefit of improving rationality due to being an evidence-based approach, and ultimately improves decision quality under uncertainty.

2.5. Big data and big data analytics capabilities

When the emergence of big data (BD) occurred, the definition was very divorced from traditional data in its very nature. 'Big' in big data does not necessarily refer to size but rather a composite of specific factors, popularly known as the three Vs. being volume, velocity and variety (George, Corbishley, Khayesi, Haas & Tihanyi, 2016). A fourth dimension had been introduced by Goes (2014), who describes the veracity of big data as an important attribute.

According to Wamba, Akter, Edwards, Chopin and Gnanzou (2015), volume refers to the quantity of data and this measured by the amount of storage space required to save, share and store the data. Velocity refers to the speed at which data is generated and given the number of data sources currently available, from social media to wearable devices, the rate can be expected to be tremendous (Wamba et al., 2015). Variety is the different types of data and the form in which it is acquired, structured, semi-structured and unstructured (Wamba et al., 2015). Veracity in Goes' (2014) definition refers to the quality of data in terms of completeness, consistency and accuracy by Janssen et al. (2017).

Typically, data is obtained in an unstructured format. This raw data needs to be analysed, cleaned and structured in a usable format in order for it to generate valuable insights and knowledge for decision makers. According to Goes (2014), big data analytics (BDA) are the use of clever methods and techniques to extract meaningful information from big data to support decision-making. Furthermore, specific skills are required to decipher this data into a usable state. This introduces big data analytics capabilities (BDAC) which are defined as the ability to of the firm to capture and analyse data towards generation of insights (Gupta & George, 2016).

Some of the benefits of big data, big data analytic capabilities and data-driven decision-making are in the form of social and economic value (Günther, Rezazade Mehrizi, Huysman & Feldberg, 2017). Social value benefits have materialised in the spheres of education, public safety, security and healthcare, with benefits serving individual and societal needs such as reduction of unemployment rates. Another sphere is the use of meteorological data to forecast weather patterns to evacuate populations in a bid to avoid catastrophes such as earthquakes, tsunamis, hurricanes and tornados. Economic benefits accrue in enhancement of shareholder value, competitive advantage and growth of client base and market share (Günther, et al., 2017).

There are some constraints to big data and big data analytics capabilities. As mentioned earlier, data quality plays a pivotal role in the quality of decisions made (Janssen et al., 2017). It is imperative that the analytics be able to provide insight into data for managers and decision makers to obtain any value from big data (Ransbotham et. al, 2016). This ability described in big data capabilities coalesces in four dimensions namely (1) mindset; (2) skillset; (3) dataset; and (4) toolset (Pigni, Piccoli & Watson, 2016).

It can be expected that uncertainty brings about critical questions for organisations to navigate the uncertainty and threat posed to business. The value generated by organisations from big data is "not merely a problem of having the right "ingredients" – the right stuff – but instead demands astute management of their systematic interaction in an organizational setting" (Pigni et al., 2016, p. 18). This could become the starting point in understanding the lack of clarity explained by Mikalef et al. (2020), on what conditions need to be prevalent for big data technologies to lead to realised value for organisations. Figure 2 below is a diagrammatical representation of the interaction of big data, big data analytic capabilities in data-driven decision making. It shows that big data is collected and deciphered using big data analytics and big data analytic capabilities into information and insights. The information and insights combined with existing knowledge, are interpreted to formulate a decision. This process is what is known as a data-driven decision-making.

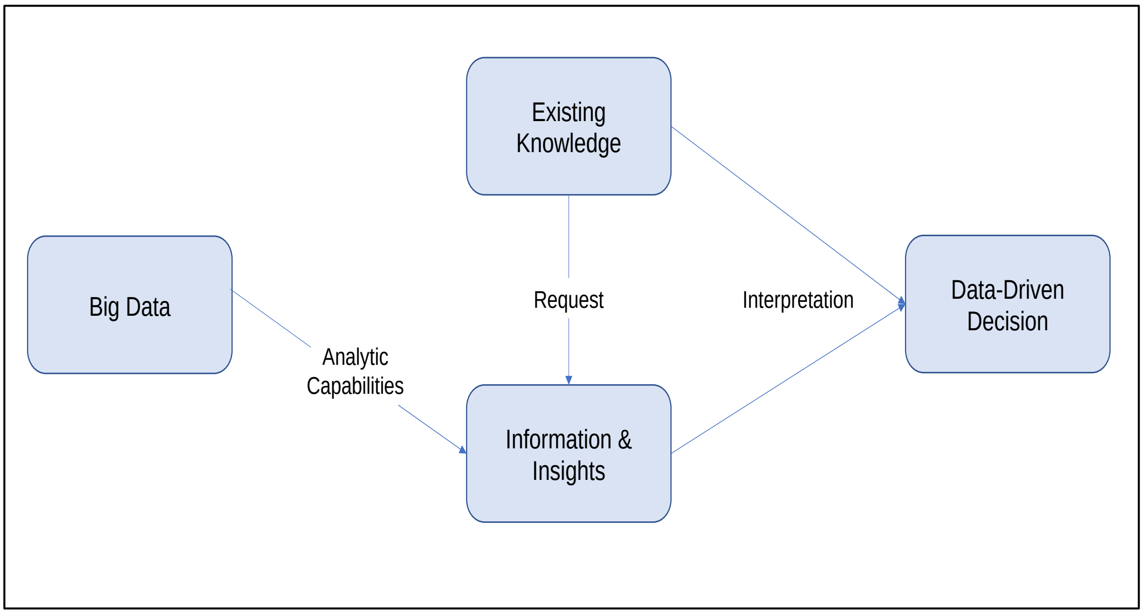

Figure 2: Data driven decision-making model

Sources: Adapted from Pigni et al. (2016)

Based on the above it is evident that big data is meaningless and useless without big data analytic capabilities and that what matters are the insights drawn from the data to support the decision-making process.

Building on from the above model, Pigni et al. (2016) identify the essential ingredients and dimensions of the data-driven decision-making process as mindset, skillset, dataset and toolset and can be presented diagrammatically as shown in Figure 3 below.

Figure 3: Dimensions of [big] data driven decision-making

Source: Adapted from Pigni et. al. (2016)

Mindset

According to Pigni et al. (2016), organisations must be willing to invest in data-driven initiatives for the upside along with the downside this may bring. This mindset comes about as an appreciation for the value digital data streams (DDS) to influence a change in organizational culture (Christensen, 2006) that encourages and promotes data-driven decision making. The additional layer to this is the creation and implementation of a DDS strategy that further fuels the keenness to invest in big data architecture. According to Hume and West (2020), the *mindset,* being the data-driven culture of the organisation must be encouraged and supported by the board and executive management team. To further emphasize the above, they further say that "a data-driven decision-making infrastructure is also essential. The organization's commitment to data-driven decision making must be evidenced by investments in the appropriate technologies and staff" (Hume & West, 2020, p. 35).

Skillset

The ability of an organisation to coordinate the activities of the organisation and business functions and technological capabilities is key to extracting value (Pigni et al., 2016). As senior managers are the personnel in the organisations that are actually making decisions, skillset is therefore considered at both individual and organisation level.

Skillset at an organisational level alludes to the ability for the organisation to convert data into improved decision-making. This speaks to big data analytics being able to provide insights into data for managers and decision makers to obtain any value from big data (Ransbotham et. al, 2016). Therefore, value “starts with a knowledgeable person requesting relevant information, followed by processing appropriate data to generate this information, assuming it is available” (Pigni et al., 2016, p. 20). The information obtained is then used to support a decision the effectiveness of which varies given that data quality plays a pivotal role in the quality of decisions made (Janssen et al., 2017).

Dataset

The characteristics of complex environment contextually are (1) flux and unpredictability; (2) no right answers; (3) unknown unknowns; (4) many competing ideas; (5) a need for creative and innovative approaches (Snowden & Boone, 2007). Uncertainty seems to mimic some of the characteristics of complexity, being the incompleteness of information that renders the ability to forecast the consequence of a decision (Bîlcan, Ghibanu, Bratu & Bîlcan, 2019). This understanding is shared by Bloom (2014, p. 154) who also states that uncertainty is “people’s inability to forecast the likelihood of events happening”.

As Snowden and Boone (2007) described the different characteristics of a complex environment in their stud, Alexander, Kumar and Walker (2018) developed a decision theory perspective on complexity in performance management, that has come to be known as the Cynefin framework. This framework is a conceptual mapping of decision process in complex and unstructured environments. The framework suggests that decisions makers ought to probe, sense and respond when making decisions in a complex operating environment (Snowden & Boone, 2007). From the study by Alexander et al. (2018), we know that a key characteristic of complex environments is uncertainty, which has been defined as the insufficiency of information to forecast or predict the outcome of certain decisions made by Maitland and Sammartino (2015).

To address this insufficiency of information, it can be argued that big data and big data analytic capabilities contribute significantly to the *probe* and *sense* requirements of the Cynefin framework for making decisions in complexity. It can be inferred that this is equivalent to data-driven decision-making in uncertainty as this is a characteristic of complexity.

In conjunction with Snowden and Boone (2007), who highlight that complexity aids current and future decision-makers comprehend advanced technologies, globalisation and market & cultural changes, Pigni et al. (2016) explain dataset is the good quality and relevant data that decision makers can use to base strategic decisions for value creation.

Figure 4 below is an illustration of the different decision domains, the characteristics thereof and recommended decision process. In Figure 4 below, the focus was on Domain 3, in which the system type is unstructured and complex, requiring a *probe, sense and respond* process to decisioning. This three-step process can be achieved by big data and big data analytic capabilities.

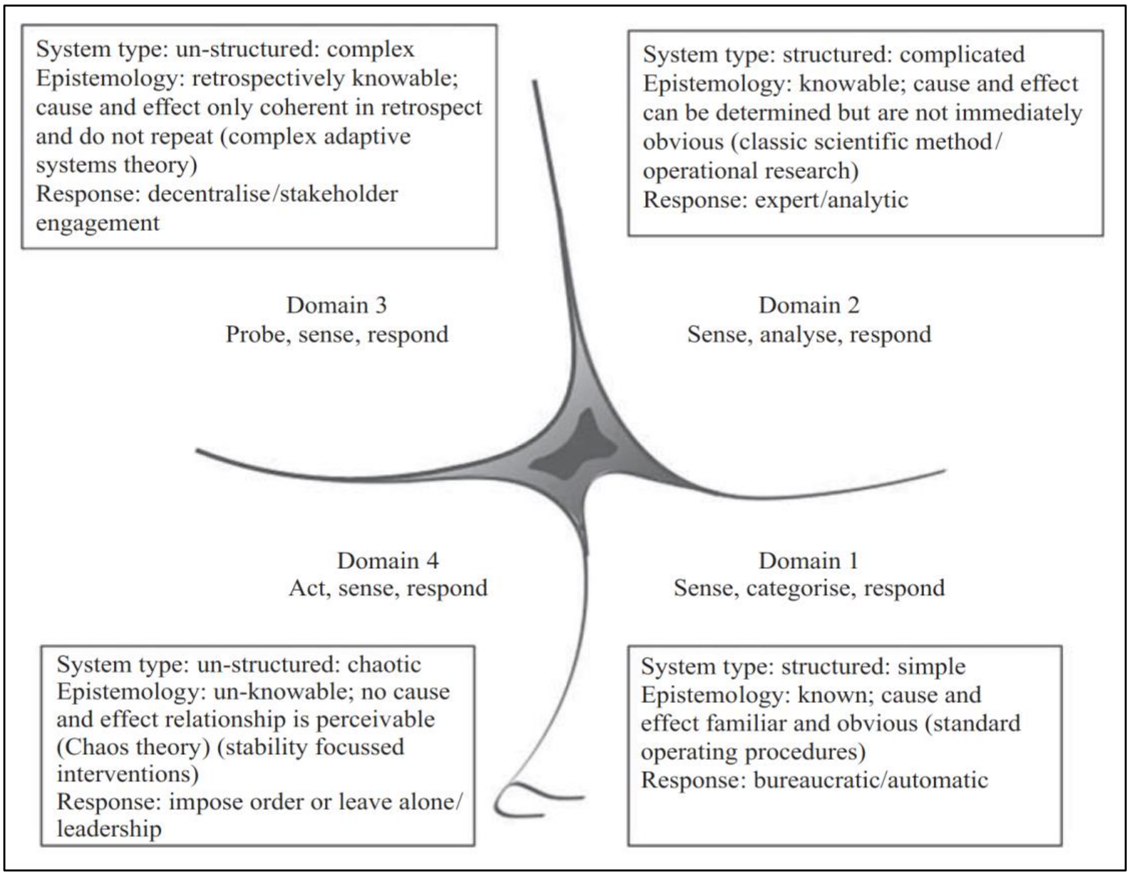

Figure 4: The Cynefin framework

Source: Alexander et al. (2018)

In the actual decision application, Figure 5 below, is an adaptation of the hierarchy of decisions and Cynefin framework, illustrating that strategic decisions are the predominantly the ones taken in the complex environments characterised by heightened uncertainty. Given the emergence of the Fourth Industrial Revolution (#4IR) (Schwab, 2016), the researcher argues for broader decision types being possible in uncertainty, beyond solely strategic decisions. According to the World Economic Forum (2016), the primary difference for decision-makers between #4IR and the Second Industrial Revolution is the non-linearity of decision making, owing to the pace of change. In reconciling Figure 5 below and #4IR, the researcher is nudged to explore the role of data-driven decision-making hoping to understand tactical and operational data-driven decision-making implications under complexity and uncertainty.

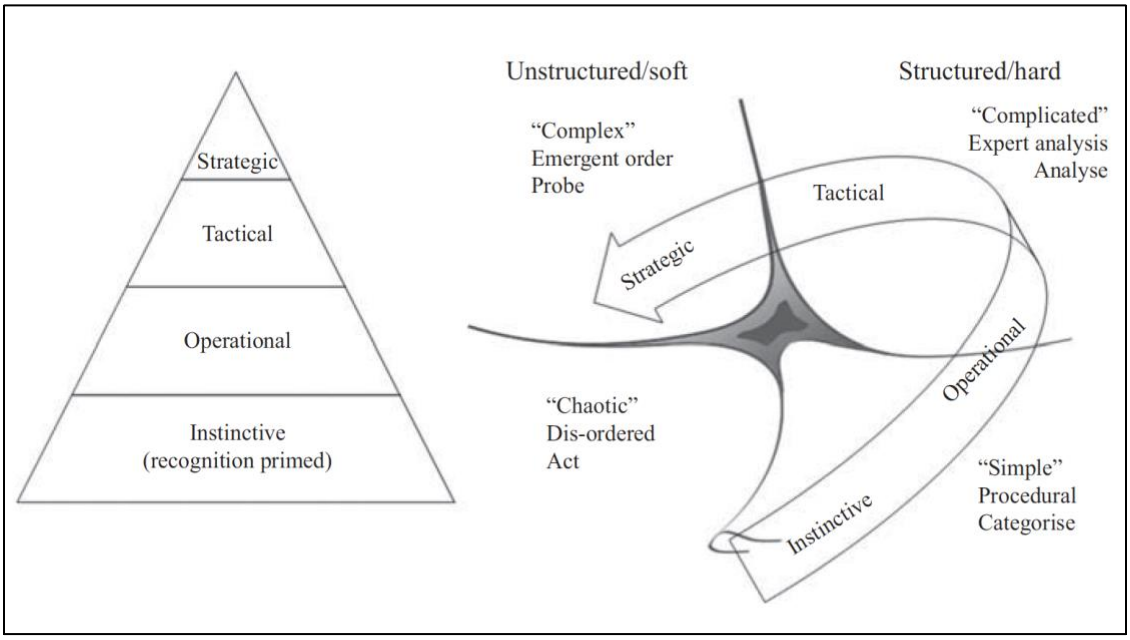

Figure 5: Hierarchy of decisions and the Cynefin framework

Source: Alexander et al. (2018)

Toolset

Toolset as would resonate with most people, is the ability to use the appropriate software and hardware to draw insights from [big] data to create value. Pigni et al. (2016) argue that believed that the toolset dimension is the most technologically based dimension, powerful enough to influence the ability of a firm to profit from digital data streams. They further describe mindset and toolset dimensions as being the core of big data initiatives and thus critical antecedents to DDS value creation (Pigni et al., 2016). Horney et al., (2010) argue that data made available on time has a positive effect on improving real-time decision-making for value creation. Therefore, it can be inferred that in VUCA environments, the timing of decision-making becomes essential for competitiveness and protection of market share which ultimately translates to value creation. Hume et. al (2020) also describe that there are tools that pull together sets of large volumes of complex raw data and present them in a simpler way for insights to be drawn for decision-making. All of these technologies that collect, integrate, analyse and present business information are also known as business intelligence (BI). This not only extends to just accessing data and insights, but also ensuring data integrity; integrity being defined as accurate, complete and consistent (Hume et. al, 2020).

2.6. Benefits of [big] data-driven decision-making

Despite there being a lack of clarity as to what conditions need to be prevalent for big data and big data analytic capabilities technologies to lead to competitive gains (Mikalef et al., 2020), literature exist that confirms the benefits of data-driven decision-making. Provost and Fawcett (2013, p. 53) explain that data-driven decision-making “refers to the practice of basing decisions on the analysis of data rather than purely intuition”. They further confirm that the benefits of data driven decision making have been realised beyond reasonable doubt.

A study conducted by Erik Brynjolfsson, an economist from MIT proved a direct positive correlation between the adoption data-driven strategies and firm productivity. This study, documented by Provost and Fawcett (2013), also showed a positive correlation with the firm’s financial measures that include asset utilization and return on investments, ultimately affecting the market capitalisation of those firms that had publicly traded stocks. This narrative was further cemented by Brynjolfsson and McElheran (2016b) who noted that data-driven decision-making is directly correlated with performance; however, the benefits are significant in organisations where supportive changes in management practices are implemented. The study was informed by data from the US Census Bureau which availed access to a large purposive sample to examine the data-driven decision-making and firm performance phenomena. A few consistencies emerged in the study highlighting a correlation between data-driven decision-making and (1) economies of scale; (2) an educated workforce; and (3) high levels of information technology investment (Brynjolfsson & McElheran, 2016b).

Big data analytics and analytic capabilities were identified as a common path to value for organisations (Kiron, Prentice & Ferguson, 2014). It is noted, however, that the exponential growth experienced by firms due to analytics has flattened out. This is attributed to the rapid uptake in analytics by competitors diminishing competitive advantage gains. However, the inadvertent benefit of data-driven decision-making is innovation and the quest thereof. This study was aimed predominantly at exploring and understanding how companies were using analytics for innovation, as a means to “create substantial business value” (Kiron et al., 2014, p. 13).

2.7. The Fourth Industrial Revolution (#4IR)

The term #4IR first came about from the Founder and Executive Chairman of the World Economic Forum in his 2016 publication titled “The Fourth Industrial Revolution” (Schwab, 2016). This revolution follows, numerically, three other revolutions, the first industrial revolution dating back to 1784. The First Industrial Revolution is stated to have used basic resources such as water and steam power to foster production using machinery; with the Second Industrial Revolution stated to be driven by electricity to scale up production and lastly the Third Industrial Revolution was characterised by information technology used predominantly to automate production processes (Schwab, 2016).

This fourth is characterised by technological advances in industries, including technologies such as 3D printing; artificial intelligence (AI); autonomous vehicles; biotechnology; cyber-physical systems (CPS); fifth-generation wireless (5G); internet of Things (IoT); nanotechnology; quantum computing; and robotics (Sutherland, 2020). Advancing from the Third Industrial Revolution, what we see in #4IR is artificial intelligence, seen in self-driving cars and drones. To emphasize the power of the Fourth Industrial Revolution, Microsoft (2020) states that Quantum Computing is able to solve complex problems that would otherwise require billions of years to solve, in just a few hours or days.

It is also noteworthy to mention that #4IR is said to have the potential to result in long-term gains in efficiency and productivity (World Economic Forum, 2016). This also has the effect of raising global income levels and improve the quality of life for citizens of those economies that adopt and stay abreast with the changes #4IR comes with. Take for example, the use of drones to deliver medicine across Africa by an African tech start-up known as Zipline (TechCrunch, 2020). What has already been experienced as the power of #4IR, is the possibility of industry disruption, as we see the retail industry today, migrating from brick and mortar to online platforms. According to Klaus Schwab, disruption would flow from the agility and innovation of competitors who would leverage on access to global digital platforms, would outperform competitors to improve the quality of products, enhance speed of delivery, offering competitive prices at the same time (World Economic Forum, 2016) and the evidence of this today is Amazon (CNBC, 2018).

2.8. Other aspects of big data

2.8.1. Data Quality

An important aspect data-driven decision-making is using quality data (Janssen at al., 2017). Günther et al. (2019) explains that this remains a fundamental challenge as data is mostly inconsistent, inaccurate, incomplete and irrelevant, owing to time delays. Timmerman and Bronselaer (2019) express multiple measures of data quality in a scientific manner. Amongst the many measures, they explain the *Seven W's* of scientific data collection and validation. They further explain the need for ensuring data quality in the presence of uncertainty and the measurement by decomposing complex uncertainty predicates to easier and simpler predicates verifiable using Boolean values.

It can, therefore, be inferred that big data analytics and big data analytic capabilities are crucial to the decomposition uncertainty, ensuring high quality data that fuels quality decision-making under uncertainty.

2.8.2. Data Privacy

In South Africa, legislation is in place to enhance data privacy and restrict the distribution of data without sufficient authority and permissive rights to do so. The specific statutory instrument is known the Protection of Personal Information Act 4 of 2013 (South African Government, n.d.), otherwise commonly known as the PoPI Act. This act has specific clauses that aim to do the following:

- the promotion of the personal information protection that is collected and by third parties;
- the establishment of provisos that will govern the processing and handling of personal information;
- appoint an Information Regulator, that has the rights, mandate and power to perform certain duties and functions in terms of this Act and the Promotion of Access to Information Act, 2000;

- establish appropriate of codes of conduct when handling and processing personal information;
- establish provisos for the processing of unsolicited electronic communications and automated decision making; (South African Government, n.d.).

In a more practical sense, the impact of the enactment of this statutory instrument is promotion of data privacy, which inadvertently is the restriction of sharing of certain information unless certain conditions are met (South African Government, n.d.). Given that these conditions are implemented at an organisational level (South African Government, n.d.), this can result in the restriction of data and information sharing between companies falling within a group of companies and/or where organisations are divisions of the same group and thus do not have access to data that may be imperative to obtaining a competitive advantage.

2.8.3. Data Skills Transfer Migration

According to Kozyrkov (2018), data analysts and/or data scientists are the most fashionable recruitments of the 20th century. This is due to the highly specialised skills that extend beyond the abilities of machine learning and artificial intelligence, despite the extensive popularity and adoption of these technologies (Kozyrkov, 2018). Given the relatively high demand for the data analyst and data scientist skill, the transferability of such a skill from origin country to destination country is characterized by lower frictional costs (Nakagwa, 2020).

Frictional costs are described as the factors that act as impediments to fluid skills transfer when an individual decides to migrate from one country to another. Common frictional costs include language differences, occupational licensure, differences in technology and culture (Nakagwa, 2020). Nakagwa (2020) further explains that occupational licensing is possibly the most significant barrier to skills portability in the skilled labour workforce. Inferring from the above statement by Nakagwa (2020), the international accreditation of data scientist and analyst qualifications, such as those administered by *Microsoft, IBM, Google, SAS and Cloudera* for example (CIO, 2020), serves as a promotional factor for skills transfer. The growing demand for big data analytic capabilities (Kozyrkov, 2018), coupled with the significantly reduced frictional costs of skills transfer for this occupation, means that South African individuals in possession of a skill in such high demand can transfer their skill to more attractive and higher earning markets.

2.8.4. Digital Data Strategy

Data is complimentary to organisational activities as it will aid decision-making processes of those tasked with decision-making (Provost & Fawcett, 2013). It is, therefore, imperative to ensure that the digital strategy of the organisation is executed perfectly to increase the likelihood of success of such an initiative. According to Goold and Campbell (2002), an organisation needs to satisfy nine tests to conclude whether the organisation is well designed. For this study, focus is on two of the nine tests, being the difficult-links test and specialist cultures test.

As we move deeper into the Fourth Industrial Revolution (World Economic Forum, 2016), the specialist cultures need to be abolished. A specialist culture, according to Goold and Campbell (2002), is the distinct culture and way of working that a specific unit or department in an organisation adopts. Good and Campbell further iterate the need for identification of such unitary forms of cultures and whether their dominance can contaminate the overall goals and objectives of the organisation. The difficult links test, on the other hand, alludes to the effortless interaction and collaboration of units or departments within an organisation. All of these tests serve a bigger goal, in ensuring that the execution of a strategy is fluid and seamless.

Sull, Homkes and Sull (2015) delved into the reasons why strategy execution fails, and they found five myths that help explain the reasons for execution failure. Perhaps the most applicable to this research is the idea that communication equals understanding. In the absence of adequate and clear communication to a point of comprehension, the myth that communication equals understanding perpetuates. In particular, a digital data strategy requires the abolishment of specialist cultures and more collaboration of the multiple units of the organisation, otherwise known as the difficult links (Goold & Campbell, 2002). For example, the IT department must have a clear mandate for ownership of big data analytics and analytics capabilities, whilst the eventual user of the data should assume ownership of the data. Regardless of where the custodianship lies, collaboration between organisational units will promote strategy execution and realisation of strategic objectives.

2.9. Conclusion

In conclusion, it has been established in the literature review that the business environment in South Africa has become complex and uncertain. This uncertainty is difficult to navigate and those tasked with decision-making need to make decisions that affect the overall survival or growth of their respective organisations. Given that the big data and big data analytics have already shown value for substantial value for organisations (Brynjolfsson et al., 2016b), in particular U.S. manufacturing firms and that analytics were used to foster innovation (Kiron et al., 2014), this becomes a good reference point on what to incorporate into the decision-making process given the impact *#4IR* (Schwab, 2016) and COVID-19 (World Health Organisation, 2020) will have on the business environment.

In summary, despite the traction and popularity gained by big data and big data technologies for decision making, as well as the benefits identified in the literature review, this literature review does not ***explicitly*** describe the role of data-driven decision-making under uncertainty, the preconditions necessary as well as what enablers and obstacles exist in a South Africa context for the same value and innovation to be realised. Therefore, the objectives of this research will aim to address this gap in literature and explore the role of data-driven decision-making under uncertainty. The following chapter will outline the specific research questions that will aim to achieve the above.

3. Research Questions

The primary reason for this research was to explore the role of data-driven decision-making under uncertainty and how it can be optimised to provide value to organisations. There is also empirical evidence of the organisational success and value obtained from big data investments and data-driven decision-making, however, this has not been explored in the context of uncertainty (Brynjolfsson & McElheran, 2016b; Mikalef et. al, 2020)

3.1. Research Question One

What are the South African senior managers' perceptions of data-driven decision-making under uncertainty?

Surveys conducted in the United States of America in the recent past showed that a number of senior managers obtained value from big data and artificial intelligence in effecting data-driven decision-making (Davenport & Bean, 2018). Research by Rejikumar et al. (2020) expresses the need for organisations to evaluate their management team's perception of data-driven decision-making in order to fully unlock its potential. Therefore, this question set out to explore the perception of data-driven decision-making by South African senior managers under uncertainty. The response to this question will guide understanding of big data, big data analytics capabilities and data-driven decision-making by senior managers and the contexts within which it is useful and/or otherwise.

3.2. Research Question Two

How are big data and big data analytics used for decision-making under uncertainty by South African senior managers?

The purpose of this question was to establish how South African senior managers use big data and big data analytics. This question was also set to explore whether South African senior managers have realised the value of data in effecting data-driven decision-making processes in uncertainty and the extent to which they place reliance on it. In the literature review, this was defined as big data analytics capabilities (BDAC), being the ability of the firm to capture and analyse data towards generation of insights (Gupta & George, 2016). Furthermore, the "ability" manifests itself as the organisation's (1) mindset; (2) skillset; (3) dataset; and (4) toolset (Pigni, Piccoli & Watson, 2016).

3.3. Research Question Three

What are the obstacles and challenges of using data for decision-making under uncertainty?

This question sought to unearth the obstacles and challenges faced in obtaining data and using it for decision-making in uncertainty. According to Goes (2014), big data analytics (BDA) entails the use of clever methods and techniques to extract meaningful information from big data to support decision-making. Horney et al. (2010) emphasize the need for agility in decision-making especially when confronted with complexity from uncertainty. Agility facilitates organisational flexibility, speed of execution and anticipation of problems allowing for timely response to the impact of uncertainty (Horney et al., 2010).

3.4. Research Question Four

What conditions encourage and enable the use of data-driven decision-making under uncertainty?

Millar et al. (2018) identified disruptive innovation as a driver of and outcome of uncertainty. Meanwhile, Wessel (2016) emphasized the power of big data in pioneering what was termed data-enabled disruption. However, Mikalef et al (2020) highlight the lack of clarity to what conditions need to be prevalent, if at all, for such technologies to lead to competitive gains. This question, therefore, seeks to explore and understand what South African managers experience as conditions that encourage and enable data-driven decision making in uncertainty and/or whether uncertainty is one of the conditions.

3.5. Research Question Five

What is the impact (advantages or disadvantages) of data-driven decision-making under uncertainty?

This question explores whether there are any distinct advantages and/or disadvantages of data driven decision-making. Ransbotham et al. (2015a) found a higher probability of generating competitive advantage for organisations when analytical skills and business knowledge are combined into data-driven decision-making.

3.6. Research Assumptions

The researcher assumed that some of the following practices, norms and assumptions were prevalent in the South African business environment:

- Despite big data and big data analytic capabilities being in existence for some time, there is limited knowledge of, understanding and appreciation for data-driven decision making under uncertainty.
- Therefore, the very practice of data-driven decision-making is not widely adopted by South African senior managers and possibly perceived as largely a Western practice, than a practice applicable in everyday decision-making and times of uncertainty.
- South African managers do not use data-driven decision making under uncertainty and rather opt to use heuristics (Artinger et al., 2014) even in the presence of data to base decisions under uncertainty. This is attributed to the absence of a data-driven culture within South African organisations.
- There is general inertia towards the adoption and use of big-data initiatives among South African senior managers and their organisations.

3.7. Conclusion

The research questions for this study highlight the necessity of understanding of data-driven decision-making under uncertainty, in a South African context. The chapter that follows outlines the methodology adopted in collecting and analysing data for this research.

4. Research Design

This chapter outlines the research design and methods adopted to achieve the intended objectives of the study. The researcher understood the essence of a concise research plan to ensure that the logic of the study and research questions are answered. Methodological choices, respondent population, unit of analysis, sampling techniques, measurement instruments, the data gathering process and analysis of results are discussed, along with the limitations of the study.

The research design was aimed at providing an exploratory study, “initial research conducted to clarify and define the nature of the problem” (Zikmund, 2013, p. 102). The researcher, through structured and semi-structured interviews sought to understand the experiences of senior managers in South Africa with data-driven decision-making when confronted with uncertainty.

4.1. Philosophy

An interpretivism philosophy was adopted for this study (Lindgreen, Palmer, Vanhamme & Wouters, 2006; Viera & Freer, 2015). Such philosophy upholds that “meaning is hidden and must be brought to the surface through deep reflection” (Ponterotto, 2005, p. 129). Thus, the research strategy included collecting data through researcher-participant dialogue capturing senior managers’ lived experiences and reflections on these.

4.2. Methodology

Saunders and Lewis (2017) espouse the value of exploratory study that it is intended to provide greater understanding and insight into the character of phenomena. This was ideal for this study as it aligned with the objective for in-depth investigation and exploration of data-driven decision-making in uncertainty. A qualitative approach allows participants to share and describe experiences of a phenomenon whilst also articulating perspective in “everyday language” (Ponterotto, 2005, p. 128). Qualitative methodology is aimed at providing the researcher access to deeper comprehension of people’s experiences that explains aspects of their actions (Merriam & Tisdell, 2016).

Invariably, responses from the experiences of data-driven decision-making for the various senior managers will have similarities and differences from one senior manager to another. This provides the richness required to formulate comprehensive insight required to meet the objectives of the study (Schurink, 2009). A qualitative research strategy, containing semi-structured questions (Saunders & Lewis, 2017) was pursued. One-on-one semi-structured interviews were conducted with participants, ensuring that the confidentiality and anonymity of responses and respondents was maintained.

An appropriate sampling technique supported the research strategy by targeting the senior managers, who make use of data to make decisions and in particular, regularly formulate such decisions under uncertainty. To ensure context was aligned, uncertainty was defined to the South African senior managers as a scenario in which the ability to know the outcomes and consequences of decisions are unknown and difficult to forecast (reference). It is for this reason that specific reference to the global COVID-19 pandemic was used to set the scene as the outcome of decisions taken during this period were difficult to predict. This strategy aligns with the interpretivism philosophy (Lindgreen et al., 2006) and further enhanced by an open approach that allowed for sharing of views and experiences by senior managers in the researcher-participant dialogue leading to deep reflection (Ponterotto, 2006).

4.2.1. Methods

A mono-method being an approach that makes use of a single data collection technique (Saunders & Lewis, 2017; Pinto, Lein, Mahoque, Wright, Sasser & Staton 2018) was used for this study. This entailed one on one depth interviewing with senior managers in medium to large organisations for whom data is an essential resource. A purposefully compiled interview guide as recommended by Viera and Freer (2015) was used to guide discussions ensuring that the data collected captured experience, steeped perceptions on the extent of and challenges with data-driven decision-making under uncertainty.

As this study was conducted, individual interviews were undertaken to gather the perspectives of senior managers on Data-Driven Decision-Making in under Uncertainty. It was preferred to have these interviews in person, but due to COVID-19 and restrictions on travel and gatherings imposed by the Government, coupled with the health and safety consideration, this was not possible. The researcher opted to rather convene and conducted the interviews virtually using online platforms such as Zoom, Skype and Microsoft Teams. An interview guide, containing open-ended questions, was used to gain the deeper insights around the phenomenon of Data-Driven Decision-Making under Uncertainty (Saunders & Lewis, 2017).

4.2.2. Time Horizon

The study was cross-sectional in nature due to the fact that it that takes a snapshot of the views of senior managers at a point in time (Saunders & Lewis, 2017; Zikmund, 2013). This cross-sectional choice time horizon was motivated by the uncertainty posed by the COVID-19 pandemic (World Health Organisation, 2020), that poses unprecedented uncertainty that has been far reaching across multiple industries.

Cross-sectional research can also be executed within limited time frames compared to longitudinal studies that require lengthy data collection (Rindfleisch, Malter, Ganesan and Moorman, 2008). Therefore, a cross-sectional time horizon was advantageous with respect to the time constraints surrounding the timing targets set for the completion of this study. This exploratory cross-sectional study (Pinto et al., 2018) evaluates the knowledge, attitudes, and practices of senior managers regarding the use of data to support decisions under uncertainty.

4.3. Population

In this study, the population was senior managers with decision-making responsibilities within South Africa. The reason for selecting this population was to identify those with decision-making authority in an organisation and regularly make use of data in supporting their decisions. It was expected that these individuals possess some form of education and insight into big data, big data analytics, big data analytics capabilities and decision-making skills, techniques and experience with making decisions under uncertainty.

The selected population was not industry specific which can be viewed as advantageous in that insights and learnings from this study could be applied across various industries.

4.4. Unit of Analysis

In this study, the unit of analysis was senior managers with experience making decisions under uncertainty. The different perspectives of these individuals provided rigour and depth to the comprehension of the phenomenon and how it was experienced at an individual level. This eliminated group think and bias in a group setting.

4.5. Sampling Method and Size

For purposes of this study, a purposive sampling technique was adopted. This technique is non-probabilistic, and judgement is employed by the researcher to select the sample based on specific requirements (Saunders & Lewis, 2012; Merriam & Tisdell, 2016). By using this sampling technique, it is expected that research questions will be answered truthfully and achieve the objectives of the study (Saunders & Lewis, 2017). The sample consisted of participants who have knowledge of big data, big data analytics, big data analytics capabilities and using data to support decision-making. These respondents also possessed some experience with making decisions under uncertainty. An initial sample size of 15 participants was selected from various professional bodies such as the Institute of Directors South Africa (IoDSA), South African Institute of Chartered Accountants (SAICA) and also by leveraging existing networks in the researcher's professional spheres and places of management education such as the Gordon Institute of Business Science (GIBS). The final pool of contributors consisted of 10 respondents.

Such revision in size is acceptable (Merriam & Tisdell, 2016), for purposive samples as data collection proceeds up to a point where no new insights are generated**.**

4.6. Data Collection Tool

In most qualitative studies, data to support the study is normally conducted through face-to-face interviews. In light of the global pandemic, face-to-face interviews could not be conducted in the interest of health and safety of interviewer and respondents. This was substituted by online platforms resulting in interviewing via Zoom. Being able to have visual connectivity with respondents allowed the researcher to establish access to probe for more information in an unstructured and flexible way. Relatedly, the style, manner and order of questions could be revised to best suit the setting ensuring that important insights were captured (Saunders & Lewis, 2017). An extract of the interview guide can be found in the appendices as Appendix 1.

Participants were neither forced nor coerced, in any way, to participate in this study. All participation was voluntary, and participants had the liberty to withdraw at any time. The interview questions were pre-tested in a pilot study with three senior managers who fit the criteria required for the purposive sample. The researcher solicited feedback relating to the interview guide to gauge the sufficiency, clarity and format of the questions as well as the overall length of the questionnaire. Additional feedback was sought from the senior managers on whether the interview guide was exhaustive on exploratory points of data-driven decision-making in uncertainty. The three participants of the pilot study were excluded from the actual data gathering process for the purpose of this study to ensure rich, unbiased data is collected.

4.7. Data Gathering Process

The data was gathered through individual Zoom interviews. Professional etiquette was observed and maintained with all participants to ensure that no part of the interview process was offensive or infringed on the rights of participants. As part of the measures to achieve this, the research proposal was submitted to the University's Research Ethics Committee (REC) for ethical clearance and approval before data collection commenced.

To ensure rigour of conversation, thought-provoking enough to stimulate in-depth insights from participants, the interview guide was pre-tested with three participants who met the criteria for the population. Overall, the interviews averaged at 40minutes long which was aligned with initial expectations that the interviews would be about 45 to 60 minutes. Audio recordings of all interviews were captured as accurate documentation of the verbatim interaction that transpired with each respondent.

4.8. Analysis Approach

Verbatim representation of findings is an important aspect of qualitative findings. Correspondingly, the audio recordings were transcribed by an independent third party. Confidentiality of the data and respondents was ensured through the use of a Non-Disclosure Agreement. The researcher then made use of ATLAS.ti, software to analyse the raw interview data. Following the guidelines of thematic analysis enabled identification of common themes. This entailed a combined inductive and deductive approach to coding each transcript. Insights from literature were used to guide the deductive assessment of the data, whilst inductive was employed when new perspective was identified that did not logically align with prior understanding.

Inductive reasoning is described as a process of moving from specific observations to broader generalisations and theories (Saunders & Lewis, 2017). According to Braun and Clarke (2006, p. 83), "inductive analysis is a process of coding the data without trying to fit it into pre-existing coding frame, or the researcher's analytic preconceptions".

In this study, the research questions were derived from literature and the identified research gap. Whilst literature shows that data-driven decision making provides social and economic value (Günther et al., 2017), it is unclear what conditions need to be prevalent, if at all, for such technologies to lead to competitive gains (Mikalef et al., 2020). Therefore, a deductive to inductive approach was relevant as the researcher started from the "bottom" from participant feedback and building "up" to theory. Braun and Clarke (2006) describe thematic analysis as a method that is iterative in nature, used to identify and analyse patterns from data; text, audio and/or visual. These patterns are then categorised into themes that are then assigned a code to which the repeated occurrences thereof are reported on. This surfaces patterns in the data which when consolidated yield themes to reveal emerging concepts.

4.9. Quality Controls

The researcher was cognisant of the need to establish and maintain quality control measures to ensure reliability and trustworthiness of the data management processes. This was important to ensure that findings and conclusions of the study were not misleading or flawed (Saunders & Lewis, 2017). Biases and process errors from participant handling and or researcher attentions affect the reliability of a study. Meanwhile, ambiguity and lack of clarity, of the research questions for example, affect the validity of data.

Therefore, quality controls were implemented that consisted of, but were not limited to, (1) testing of interview questions through a pilot study as mentioned in section 4.5 above. This was intended to ensure veracity and rigour of questions whilst mitigating the risk of ambiguity and redundancy in responses (Creswell, 2014). Secondly, conducting the interviews around the same time served to reduce the potential impact of variation in external factors when processes are implemented over a protracted timeframe (Creswell, 2014).

An iterative process of reviewing and aligning insights from literature with the results from the interview was applied. Secondary data in the form of scholarly and other new articles on emerging trends and current global news was used to triangulate the findings and reveal phenomena further, thus enhancing quality and enriching the understanding (Saunders & Lewis, 2017).

4.10. Limitations of the Design

Potential limitations for the study included the following:

- Typical of qualitative investigations, generalization and transferability was limited (Creswell, 2014). This was further exacerbated by the fact that the study was conducted within South African organisations and decision makers, a specific geography of focus.
- Purposive sampling has inherent limitations in its nature and posed a risk of excluding participants that could provide valuable insights to this study (Saunders & Lewis, 2017).
- A cross-sectional time horizon could have rendered data-driven decision-making inappropriate for some context of uncertainty.
- Participant's personal nature could inhibit accurate and/or truthful responses. Examples of these include character traits, introvert v. extrovert and/or general interview anxiety.
- The interviewing technique normally changes from one participant to another and this could yield responses. Unfortunately, probing could not be calibrated for consistency as by nature the contributions of qualitative participants are diverse.

5. Results

5.1. Introduction

Interviews were conducted with 10 South African senior managers and this process provided valuable insights into the concept of uncertainty. Perception of decision-making processes during such periods, with a strong emphasis on data-driven decision-making were also priority themes. This chapter, therefore, presents the results obtained during the data collection process explained in Chapter 4 to answer the research questions proposed in Chapter 3. These research questions were:

Research Question One: What are the South African senior managers' perceptions of data-driven decision-making have under uncertainty?

Research Question Two: How are big data and big data analytics used for decision-making under uncertainty by South African senior managers?

Research Question Three: What are the obstacles and challenges of using data for decision-making times of uncertainty?

Research Question Four: What conditions encourage and enable the use of data-driven decision-making under uncertainty?

Research Question Five: What is the impact (advantages or disadvantages) of data-driven decision-making under uncertainty?

This chapter will present the results from this analysis, along with a presentation of the themes that emerged through the interviews conducted.

5.2. Summary of Interviews

A total of 10 interviews were conducted with South African senior managers responsible for making tactical, operation and strategic decisions related to their businesses, divisions or departments. Specific emphasis was on exploring decision-making process during periods of uncertainty and the value of data-driven decision-making under uncertainty. As this research was conducted in the calendar year 2020, marred by the COVID-19 pandemic, all interviews were conducted remotely, via the online meeting platform Zoom aligning with interviewees' convenience.

The respondents were purposively selected and participated voluntarily in the interviews explaining their use of data to support decision-making. To ensure rigour and richness of conversations, diversity in terms of age, gender, race and management tenure was established in the sampling. Below is a tabular presentation of respondents and the respective positions held in organisations.

Table 1: Respondents by industry, position and management tenure

#	Industry	Position	Management Tenure
RN	Manufacturing	Finance Manager	10 years
RBr	Financial Services	Business Development Strategist	6 years
RB	Management Consulting	Client Manager	5 years
RSt	Financial Services	Chief Information Officer	13 years
RMa	Banking	Partnership Funds Manager	5 years
RM	Asset Management	Portfolio Manager | Executive	7 years
RS	Management Consulting	Principal Consultant	10 years
RL	Insurance	Actuary | Enterprise Risk Officer	8 years
RM	Banking	Digital Products & Client Systems	8 years
RT	Banking	Head of Information Risk	8 years

As the research was aimed at exploring the phenomena of data-driven decision-making in uncertainty, the interviews were semi-structured to encourage unearthing deep insights around this phenomenon from the interviewees' experiences.

As stated in Chapter 4, all interviews were conducted online and recorded to maintain consistency. These were independently transcribed for thematic analysis using the appropriate technologies. A summary of the recorded interviews is detailed below:

Table 2: Summary of interviews

Descriptor	Unit of Measure
Number of Interviews	10
Total Duration of Interviews	394 minutes
Average Interview Duration	38 minutes
Duration of Shortest Interview	30 minutes
Duration of Longest Interview	60 minutes

Code saturation was achieved at the fifth respondent, as seen in Figure 6 below. A spike in codes created was however experienced after this, mainly from respondents six and eight due to the richness of the responses revealed.

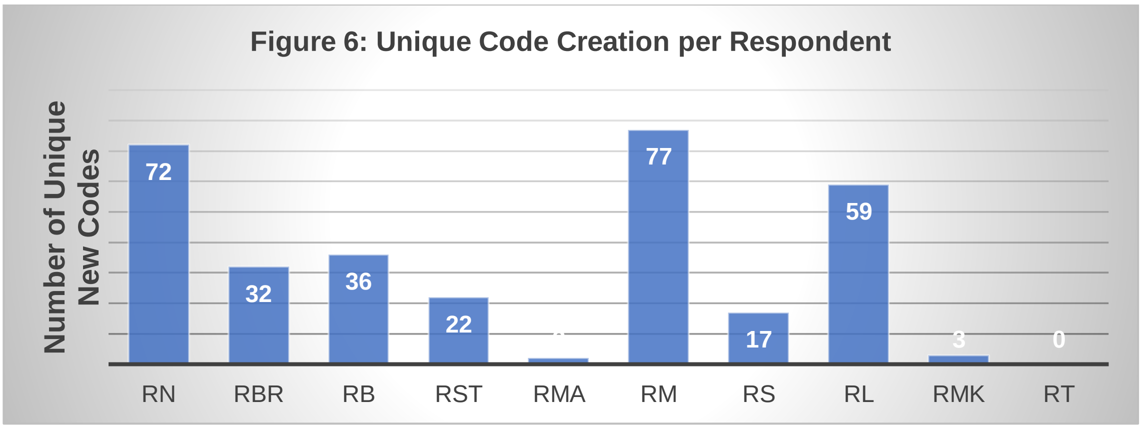

Figure 6: Unique code creation by respondent

Source: Author

A thematic analysis was conducted on the data as a suitable method to understanding the perception and experiences of South African senior managers using data to support decision-making processes. A considerable amount of time was spent reading through the transcribed interviews to get acquainted with the data as a first phase. In the second phase, thought was applied to the raw data that emerged from the interviews in a bid to develop “first order codes”. Coding was done in ATLAS.ti, software that facilitates the digesting of data by assigning code to words and phrases. Iteratively engaging literature, codes were developed and identified in the interview transcripts that conjoin to the research objective.

In the third phase, a search for themes was conducted from the “second order codes” using words and phrases. The fourth phase involved a detailed analysis of the themes for completeness, leading to the fifth phase which entailed creation of final themes that provided in-depth understanding of the role of data-driven decision-making under uncertainty.

The themes developed are explained in the sections that follow below, tabulated and explained according by research question, as well as supported by direct quotations extracted from the interviews with respondents, to highlight their lived experiences resulting in the theme developed.

5.3. Research Question One

What are the South African managers' perceptions of data-driven decision-making have under uncertainty?

This question was set to explore the perception of data-driven decision-making by South African senior managers under uncertainty. Table 3 below shows the perception of the impact of COVID-19, in this context being the instigation of deep uncertainty across business and society at large.

Table 3: Respondent perception of data-driven decision-making in uncertainty

COVID-19 and Data Use	Number of Respondents	Participant ID
Enhanced the Use of Data	7	RN; RBr; RMa; RS; RL; RMk; RT
No Change	3	RB; RSt; RM
Less Use of Data	-	
Total Respondents	10	

5.3.1. Uncertainty and Use of Data: Enhanced Use

During the interviews, respondents were asked whether COVID, as a driver of uncertainty, had contributed to changed use of data. A number of codes associated with lessons respondents had drawn from data were identified and these were developed further into second order codes and eventually concluded the thematic analysis with the creation of conceptual themes which broadly explain South African senior manager perceptions of data-driven decision-making under uncertainty.

During the interviews, the respondents alluded to COVID being an accelerant of data analysis and trend analysis. It emerged that data was a pertinent component of decisioning in recent times of uncertainty, fuelling the popularity of data analytic tools analysis of customer behaviour which has become critical to protect and grown market share. The following are some of the key quotes from the interviews.

> "*I think you know the big point that has come out of COVID* [uncertainty] *is the analysis of data. So historical data, it is the analysis of data that has already been recorded. So, it's historical data that has been the primary source for COVID actions going forward."* (RN)

> "Ja, *data is a priority*! I think daily dashboards with sales numbers, you know it is driving the discipline and the behaviour within the organisation. Individuals… are coming back online or coming back and working 8 to 5 you know schedule, and now they are *trying to push the targets*, so it is driving, *the data is driving the discipline and the behaviour of the organisation*." (RN)

Furthermore, the results reveal that uncertainty has been a key driver for use of big data and data analytic tools and capabilities. This is largely attributed to the very characteristics of uncertainty, being "unknown unknowns". The respondents felt that uncertainty had disrupted confidence in what was known and whether it was still applicable. This motivated for a greater need for big data to assess megatrends and how these would impact the South African business landscape. In particular, respondents RBr and RMa, who from the financial services industry specifically indicated the importance of data to evaluate credit worthiness, liquidity and solvency of clients amid uncertainty. This is critical to the risk assessment procedures of the organisations that they are employed at. Some notable quotes from the interviewees are as follows:

> "Ja, so definitely. *I think it has enhanced the use of data so you will find that because this scenario that we find ourselves in is essentially unprecedented, what we thought we knew might not apply anymore.*" (RBr)

> "With the *prevalence of COVID what we have realised is that there is a lot of information gap with respect to the types of prices that the farmers would be able to get for their products.* Some of our exporting farmers with the market closed, projecting what their revenues are going to look like in a two year/three-year window period, to provide loan funding to them, has been quite difficult. But we have tried to do – which is really...*modelling in the dark if one can say that; is try and look at what we would call a start-up norm; so, looking at what has the industry benchmark been over a five year for somebody who starts out today.*" (RMa)

Respondents from consulting services sector perceived the use of data, under uncertainty, largely for forecasting and predicting likely outcomes into the future. It was noted that uncertainty enhanced the use of data, particularly to strengthen the value added by these consulting firms to the clients who have engaged them. The use of data to support the decision-making process has mostly helped consulting firms add value to clients by depicting scenarios, scenario planning and strategic foresight. One specific example is the respondent RL, who made specific mention of the scenario planning and strategic foresight data rendered for a specific client who was a pension fund. However, the respondent also highlighted that whilst the uncertainty has emphasised the use of data, there is need for consideration of other qualitative aspects beyond data.

> "So, it has *strengthened the already existing role of data that we have been using, but now it's like a bit more pronounced,* where we say, okay, we definitely need to think about these different scenarios. I mean, what is it that's going to happen? Because no-one is aware, or no-one knows really the future; because right now they're talking about… for example, *there are so many scenarios where you need data to capture certain decisions.*" (RL)

5.3.2. Uncertainty and Use of Data: No Change

As the research was conducted, it was noted that three of the total respondents did not experience any change in the use and/or need for data to support the decision-making process. The reasons for this perception have been summarised in Table 5 below.

Table 4: Reasons for data-driven decision-making in uncertainty

Respondent	Reasons for perception of no change
RB	Firm has already been highly reliant on data even before current uncertainty.
RSt	Organisation's environment of business is in itself already highly characterised by uncertainty. Therefore, data, data analytics and analytic capabilities are part of the business.
RM	The firm's industry is that of minimizing risk to generate a return. It is always future orientated and that in itself is uncertain.

Table 4 is a summary of the reasons some respondents did not perceive any change to the use of data due to uncertainty. It is important to note, however, that did not mean that data is not valuable or useful under uncertainty, but rather that their organisations were already invested in big data and big data technologies before uncertainty, as a performance condition within their industries.

Respondent RM, who is employed as a portfolio executive and executive director in an asset management firm, indicated that data was always an integral part of their business processes. Having investments on major stock markets meant constant exposure to uncertainty which provided valuable lessons on the value of risk management practices as opposed to enhancing the use of data. A specific quote from respondent RM on this was:

> "Yeah, so I'd say it's *not much of a change.* What it has done *is it reinforced the idea that those fringe risks that's still coming, come true.* So, the risk, or the uncertainty of having a pandemic, you know, any risk model would have shown you that risk and chance, their impact; so, to say that it was unforeseen that you'll have a pandemic isn't probably entirely accurate – *there is always a chance, but until it comes true you assume it's never going to happen.*" (RM)

Respondent RSt on the other hand, explained that big data and data analytic capabilities were an integral part of their operations as they predominantly operate in an environment of uncertainty. It is, important to note that respondent RSt is employed as a chief information officer (CIO) and intimately understood the value of big data and big data analytics.

> "So, in terms of uncertainty*, we have always operated in uncertain times*, unrelated to unprecedented uncertain times, so uncertainty in our world is that avoidance is a huge issue, so we are uncertain of when we will get hold of the person or whether we will get hold of the person. *We use data analytics machine learning, predictive analytics* to work out things like you know the best time to call a person and things like that." (RSt)

5.4. Research Question Two

How are big data and big data analytics used for decision-making under uncertainty by South African senior managers?

The second research question explored whether South African senior managers have progressively adopted the use of big data and big data analytics to which they have realised value under uncertainty. It was noted that nine of the 10 respondents, being senior managers, do not personally operate big data analytics processes to extract data, however they have led their teams and organisations in adopting big data strategies for information. Also underway are efforts to invest in big data analytic infrastructure or at the least investing in sourcing credible, reliable and quality data to support decision-making processes.

Only one respondent, who led information risk management in a banking environment, had more intricate perspective into big data analytics, with a detail on how this generated insights required for decision-making.

> “Yes, internet of things. Because those are like the *sensors where I can apply sensors and then collect data points and then aggregate information* and then they tell you how effective the control is. But currently it is subjective.” (RT)

The rest of respondents made use of data already retrieved by analytic technologies and/or processed by specific internal departments. In other instances, respondents alluded to using data sourced externally and used for application to different types of decisions.

Respondents in manufacturing contexts confirmed the use of big data to support *strategic* decision-making under uncertainty. Such instances include funding decisions; product positioning such as make or buy decisions; and market diversification choices. Some quotes from the interviews regarding the use of data to support *strategic* decision-making.

> “Okay, so yes, the ‘when’ is really in decision making, so when we are deciding *whether to provide funding* to a farmer or not, also when we are deciding whether to provide relief to a farmer or not.” (RMa)

Employ of data to support *strategic* decision-making in the banking industry was reported to occur along multiple streams of application. It emerged that data, from an asset management perspective, is used to firstly assess specific portfolios and motivators for investment criteria. Secondly analysis of performance, drivers and indicators on different investment scenario are effected. These outcomes are used to consolidate proposals and feedback to clients. In the event that a client is agreeable on the *investment strategy*, data is used to monitor and evaluate ongoing performance and track this against other asset classes. Notably the use of data driven insights was confirmed to have markedly increased as market uncertainty was perceived to escalate. A quote from respondent RMk is below:

> "So, the virtual interaction is different from the physical one, so *pre*; I still use data but more of it now because I rely on it to guide me *during* a virtual interaction. I am then *post*; afterwards, is to say from the interactions we have had with the clients, what type of improvements or activity it did bring. So that is the monitoring and evaluation part of it. So, there is *pre; during* and *post* where I *rely on data much more* than I would have before" (RMk)

Furthermore, the results from the interviews showed that data is used to *analyse*, *monitor* and *predict* performance trends under uncertainty. The extension of the trends analysed, monitored and predicted are micro- and macroeconomic. For example, respondents who were engaged in consulting made extensive use of data for modelling scenarios and predictions of possible financial performance under uncertainty and how this may be navigated in decisioning. A quote extracted from the interviews is shown below:

> "We normally do what you call *asset and liability modelling*, that we do, and in most cases, it informs those people who are going to actually be investing money. Imagine in a period of *high uncertainty*, sometimes you've got *incomplete information*, but you just have got indications that… I mean, I think we're thinking that the market is going to go this way, so as an organisation, or *as an advisor*, you need now to say, okay, I think because of this, maybe you can go on to make this decision." (RL)

Further probing of the interview question linked to this research question asked respondents *when* they rely on data to support the decision-making process. It emerged that reliance placed on data is conditional on the credibility of the source of the data. Respondents were aware that in-house data infrastructure is expensive and that their organisations would need to invest material financial resources to get this in place. It also appeared that all respondents made use of both internally generated and externally sourced data.

Respondents in banking highlighted the use of data generated and made available by the respective banking institutions. Respondents RBr and RMk converged on this view with the quote below capturing the shared sentiment:

> "So, we understand both sides of the equation, so we do have *some of the data internally* but to your point, for looking at other markets that were at different stages in this, *we would then have to look at getting external sources of data*. So, it is a *combination of both internal and external,* and I guess a lot of *access to software* that allows us to get insights as to what is happening around specific themes globally." (RBr)

Related perspective was from a respondent from financial services. The respondent explained that despite having data analytic capabilities in-house, they made use of both internally generated and externally sourced data:

> "Look to be honest it is sort of an ecosystem. … so, there is *certainly an inhouse development capability* but in saying that we also do *rely on third party service providers*." (RSt)

It is also imperative to note that multiple respondents used multiple sources of data as a means to test the veracity of the data and the insights that can be drawn from this data. This finding adds to the answer of *when* South African senior managers use data to support decision-making processes. It is also implicit that the multiple data sources are all aimed at extracting *relevant* data. Some quotes on this are below:

> “We see it in our industry where there’s lots of data around and it’s very, very difficult to know *what’s relevant and what’s not relevant* – and that’s something that us as humans have to do. So, if you can get a way of having *a machine really know what is relevant and what’s not relevant*, it will definitely improve the decision-making.” (RM)

> “Because if you just rely on one data source, I mean that is *a* point of view, so we *actively look for data that would contradict, and if it doesn’t contradict and it agrees, we always try to triangulate,* from at least three different independent sources. And if those tend to agree then we have some level of comfort that okay, that is potentially what the data is telling us. But if it doesn’t agree then we need to investigate further.” (RS)

Table 5 presents a summary of the big data used by South African senior managers, along with the application in terms of type of decision made. It was noted that all respondents used data to support the decision-making process of one or more of the above decision types under uncertainty.

Table 5: Types of data used for decision making

Application	**Examples of Big Data Used**
Operational Decisions	• Historical Financial Data; Efficiency Data; • Export Market Data;
Strategic Decisions	• Country Data; Macroeconomic Data; Foresight Data; Stock Market Data; • Customer Data; Real-Time User Data; Back Casting Data; • Anti-Fraud Technologies; Cyber Security Data; Information Risk Data;
Tactical Decisions	• Customer Data; Microeconomic Data; • Impact of COVID.

5.5. Research Question Three

What are the obstacles or challenges of using data for decision-making during times of uncertainty?

The third question was coined to explore the different challenges that the different South African senior managers experienced when using data to support their decision-making processes under uncertainty. Table 6 below is a summary of the challenges experienced by respondents when making use of data-driven decision-making under uncertainty.

The findings reveal a number of distinctive challenges experienced by South African senior managers when using data to support decision-making processes under uncertainty.

Access to data was a prevalent concern amongst respondents, who all cited similar challenges. In terms of access, it was revealed that sharing of data is limited across firms, whereas in another, rigid application of statute hindered the sharing of data. In this regard, this was in relation to the Protection of Personal Information (PoPI) Act 4 of 2013 was a major deterrent to sharing of data.

> “The other issue is now in terms of *PoPI*, it makes it *more difficult because data can’t be shared*. So even if it is me, for example and it is my account with like retailer X and you are now working with retailer Y, you can’t use the information from retailer X to enrich the information from retailer Y.” (RSt)

The results also revealed the challenge of data as quality and relevance of data was in multiple dimensions, mainly (1) accuracy; (2) integrity; (3) comprehensible; and (4) timeliness of data. Most respondents experienced the challenge of data relevance in different ways, yet the theme of the challenge remained the same. Whilst data quality was a challenge that emerged amongst most respondents, the measurement of quality is known to be highly subjective. It was inferred that data quality could be transposed to the combination of data accuracy, integrity and comprehensibility. These experiences by South African senior managers are expressed in the quotes below:

Dimension	Quotation
Data accuracy, integrity and quality:	"So, *data integrity and data quality* are a massive problem in basically all the banks. The reason being, there's various legacy systems, there's a lot of processes, there's a lot of *data manipulation,* there's a lot of *manual entry of data and manual capturing of data*" (RB)
Comprehensibility:	"Yes, and then *it is always easy to default to what you are used to if the new or the different is not as easily accessible nor understandable*." (RMa)
Timeliness:	"I wish I could just get all this information *at the click of … well a click of view, one or two clicks then the information is just here right in front of me*." (RT)

The primary challenge that was noted amongst all respondents was the timeliness of data. This was explained as extremely important in times of uncertainty, where the rate of change and complexity is quite rapid. It was noted that respondents converged on the notion that real-time access to data would significantly improve business responses through strategic and tactical decision-making under uncertainty.

> "I think also, the other challenge is, what I've noticed is, *there are companies that do not have the capability to provide real-time data*. So, there is a lag; there is a *time lag*. But if you use that data that you have at your disposal, it can inform you. I mean, it removes also an *element of bias* that also exists, I mean, it's *inherent in us*." (RL)

> "Ja, so Munya I think the biggest challenge – and if you are talking about a crisis environment like we have had with COVID for instance – the biggest issue from my experience is *access to real time data*, that is it." (RS)

Table 6 below shows a summary of the challenges the respondents faced, further categorised by themes.

Table 6: Challenges with data-driven decision making under uncertainty

No.	Challenge Experienced	Theme
1.	Organisational cultures and politics results in reluctance to share useful data across functions or departments.	Sharing of data
2.	Generally, even more so under uncertainty, data obtained is subject to interpretation and may result in differing and/or conflicting decisions taken.	Interpretation of data
3.	Generally, even more so under uncertainty, data collected needs to be relevant for it be useful.	Relevance of data
4.	Under uncertainty, data often comes in sporadically and only gives a "piece of the whole picture" and may lead to incorrect decisions made.	Real-time data
5.	Under uncertainty, there is often inconsistencies in quality and credibility of data, sometimes due to manipulation or human intervention.	Quality and credibility of data
6.	Under uncertainty, insufficient, relevant information introduces a need for human intervention which brings an element of bias.	Objectivity of data
7.	Under uncertainty, change is rapid and real-time data is seemingly lagging behind to offer value in timely data-driven decisions.	Real-time data
8.	Generally, [big] data comes in large volumes that are raw, is expensive to collect and/or obtain and "sanitize" for good use.	Interpretation of data
9.	Under uncertainty, the trends take time to emerge and therefore, adds to the difficulty in calculating probabilities on the [uncertain] future.	Prediction through data
10.	Generally, most organisations and/or South African senior managers do not possess the skills to collect and make effective use of [big] data.	Skills for data usage

In conclusion, data access, timing and quality (represented by accuracy, integrity and comprehensibility of data is still a challenge in South African organisations as evidenced by experiences of South African senior managers.

5.6. Research Question Four

What conditions encourage and enable the use of data-driven decision-making under uncertainty?

This question explored what respondents believed were factors that could encourage and enable, if not propel the use of data to support decision-making processes under uncertainty.

The results revealed that data-driven decision making under uncertainty requires an integrated data-driven strategy. This is implemented via (1) suitable appointments to drive the strategy; (2) investment in big data and big data technologies; (3) upskilling decision-makers; (4) standardization of data quality; and (5) organisation-wide integration of big data technologies. All the above form the artefacts for a data-driven culture within the organisation (Christensen, 2006).

The appointment of suitable data strategy stewards was a result that was noted by two respondents. These appointments are believed to be instrumental for conditions that encourage data-driven decision-making under uncertainty. Similarly, so too is the belief that data stewardship ought to be a separate department in an organisation.

> "So, you would see that most companies now would have a *Chief Data Officer being part of the Exec Team and that is a very strong signal to the rest of the organisation that actually data is a big part of our business*; without it we can't make necessarily sound decisions." (RS)

However, in assigning stewardship to a separate department within organisation structures, a clear mandate ought to be defined. One respondent felt that this separate "department" ought to focus solely on big data technologies rather than data. The respondent did explain that the actual data mining and/or extraction, leading to insights drawn from data ought to live with whoever requires the data.

> "Because I found that *IT tends to prioritise technology*, they are not thinking about the *business need, what my needs are, and how this is going to make my job or improve my decisions and priorities*, and exactly what you said earlier on, the scenarios, what can I do out of this data capabilities." (RT)

Further results and findings from interviews highlighted the need for increased investment in big data and big data technology related resources. The resources identified by respondents were hardware and software, along with the investment in human capabilities. The following key quotes have been extracted to demonstrate the actual responses solicited in the interviews.

> "I think definitely what we are seeing now is *there is a need to increase spend or visibility in this particular area*, because there is a lot that can be sort of uncovered from the data." (RBr)

> "*Refresher training sessions and then obviously in the onboarding as well*. So, I would say it is pretty well communicated throughout *all levels of the organisation how important data* is to us, and mostly how important data security is as well." (RSt)

In addition to quality control and assurance methods, investment in resources, standardization and harmonization of the credible data sources were revealed as imperative to the success of any data-driven strategy. Respondents RM and RL converged on this view, reinforcing the need for executive management to build a data-driven culture within organisations:

> "So, you *build your matrix, so you know exactly what your parameters are* and if it's outside of those parameters then you buy, if it's inside the parameters do X. And if you don't know, *if you hadn't thought about this in a time of being unemotional*, there's *no ways you're going to be objective during a time of crisis when you are emotional or you're under pressure*" (RM)

> "So, the starting point is to actually *not have fragmented data sources*. Make sure that when you're *designing your management information system, it has to actually be integrated to a number of systems* that are not talking to each other; because in *uncertain times you actually want to see or use data that's actually been taken from a given source*." (RL)

Table 7 below gives a summary of the opportunities for the enhanced use of data-driven decision-making under uncertainty.

Table 7: Conditions that encourage and enable use of data for decision making

No.	Encouraging and Enabling Condition	Theme
1.	Organisational paradigm shift towards a big data, big data analytics and a digital culture.	Data-driven Culture and Leadership
2.	Enhanced accountability at organisational level through key appointments of Chief Data Officers and/or Chief Information Officers.	Data-driven Culture and Leadership
3.	Increased spend and investment in big data analytics and a big data analytics capability via an informed Digital Strategy.	Data Ecosystems
4.	Training of the decision-makers' abilities with a specific focus on rationality and bias awareness.	Data Ecosystems
5.	Harmonisation of standards and data quality assurance procedures for the use of data to support the decision-making process.	Data Ecosystems
6.	[re]Design of Management Information Systems (MIS) to integrate firm systems to build a data ecosystem.	Data Ecosystems

5.7. Research Question Five

What is the impact (advantages or disadvantages) of data-driven decision-making under uncertainty?

This fifth and final question explored the impact of data-driven decision-making for South African senior managers. One of the impacts of data-driven decision-making under uncertainty was experienced as providing reliable insights through big data technology's ability to track data over long periods of time. In so doing, most respondents experienced data-driven decision making as a moderator and advocate for rational decisions. Subjectivity is reduced and decisions cannot be manipulated in favour of underlying bias:

> "I think the benefits are definitely that its *objective decision-making* that's taking place. It's *very difficult for people to drive agendas and for people to manipulate decision-making* processes or decision-making, if the data says other words." (RB)

> "I would say, at least it *avoids also these, I mean, a bit of knee-jerk reactions*, which actually can happen when you don't have data to support your decisions. So, for me it has been *very helpful to actually say, okay, hold back, and say, no-no-no, what we are thinking is not what the data is saying*." (RL)

As complexity is characterised by uncertainty, requiring decision makers to probe, sense and respond, respondents experienced a positive impact of data in their decision-making processes through data enabled scenario-planning. Consequently, this ability was seen to be a source of competitive advantage and possibly maintained growth in uncertainty. The following quotes are extracted from the respondents' interviews and demonstrate their lived experiences.

> "So, look the *data has been useful in allowing us to pre-empt* what is coming down the road, right?" (RBr)

> "So, like I said we started a billion Rand turnover organisation last year, pre COVID, *so we are the biggest debt collector in SA, so I mean it is the technology led and data analytics* driven heart of the organisation that *helped us to get where we are*." (RSt)

The impact of data-driven decision-making in uncertainty is summarised in Table 8 below:

Table 8: Benefits of data-driven decision making under uncertainty

No.	Impact	Theme
1.	Under uncertainty, the ability to track data over long periods of time contributes positively to improving reliability of insights.	Reliable insights
2.	Under uncertainty, quality data, contributes to overall enhance accuracy of decisions taken.	Accurate decisions
3.	Under uncertainty, data facilitates rationality and enhances objectivity on decision-maker.	Rational and objective decisioning
4.	Under uncertainty, data allows for development of multiple decision options and facilitate the weighting thereof.	Identifying options
5.	Under uncertainty, data facilitates the reduction of uncertainty through the enhancement of probability of the outcome decisions.	Reduction of uncertainty
6.	Under uncertainty, data mediates against subjective human influence and bias on decision-making.	Mediation of bias and subjectivity
7.	Under uncertainty, big data, supported with the adequate analytic infrastructure, allows for decisions to keep up with the pace of uncertainty.	Rapid decisioning
8.	Data can the accelerate and propellant of growth if paired with appropriate infrastructure to inform sound strategic decisions, even under uncertainty.	Strategic navigation

6. Discussion of Results

6.1. Introduction

This chapter will seek to establish the answer to the research question based on the interviews conducted and results obtained. The purpose of this research has been to explore the role of data-driven decision-making under uncertainty and how it can be optimised to provide value to organisations. The preceding chapter presented the results obtained from the interviews conducted with 10 South African senior managers. These results in Chapter 5, in conjunction with established literature presented in Chapter 2, will form the nucleus of the discourse on emerging outcomes from this study.

6.2. Discussion of Results for Research Question One

Perception of Data-Driven Decision-Making under Uncertainty

The purpose of this question was to explore and understand how South African senior managers perceive data and its ability to support decision-making processes in the context of uncertainty. The current global health pandemic of COVID-19 and its impact on the local and global economies presented a fortuitous backdrop of uncertain conditions that were relevant to the aims and outcomes of this study.

Qualitative perspective provides access to rich diversity of views; thus, the outcomes of the interviews and responses for the research questions were carefully examined to identify themes that were pertinent in answering the set research questions. The analysis resulted in the emergence of five core themes as follows:

1. Navigating Uncertainty (VUCA);
2. Predicting Events and Outcomes;
3. Decision Moderator and Advocate for Rationality;
4. Skillset and Mindset Required; and
5. Toolset and Dataset Required.

Each of the themes identified above will be discussed below in relation to current literature and findings of this study.

6.2.1. Navigating Uncertainty

Chapter 5 presented multiple permutations of findings. One tabulation related to the impact of context, revealed that seven out of 10 respondents experienced an enhanced use of data to support the decision-making process under uncertainty. The data in this particular context, appeared to be data used for various types of decisions ranging from strategic; operational; tactical; and in some instances, investment decisions.

On the other hand, a few respondents experienced little to no change in the use of data-driven decision-making approaches under uncertainty. It is important to note however, that the little to no change was not due to the limited value that data-driven decisions offered in uncertainty, but rather because the organisations they worked for had already invested in data analytic technologies due to their operating environments that already proved to be uncertain. Therefore, there was no need for additional interventions related to COVID-19 conditions.

These results align the counsel by Daly (2016) that managers ought to adopt a few strategies to navigate uncertainty in their decision environment. Some of these strategies include (1) delaying action to source more information and data; (2) deeming uncertainty inexistent; (3) intuitive action; and (4) investing time and effort to assess consequences and probabilities. This view is an extension of an earlier study by Lipshitz and Strauss (1997), who also argued that the standard procedure for coping with uncertainty is the application of the “R.Q.P Heuristic”. This is *reducing* uncertainty by performing a thorough and rigorous information and data search. Secondly, *quantify* the uncertainty that cannot be reduced; and then *plug* this uncertainty with a carefully designed course of action.

A common theme across both of the studies was the need for a rigorous and thorough data search before making a decision when confronted with uncertainty. The results in Chapter 5 that showed that most of the respondents experienced and enhanced use of data to support the decision-making process is testament of the literature above. Those that did not have this experience were already immersed in existing use of data based on the uncertain business environments in which their business operates. It would, therefore, appear that South African senior managers have grown an appreciation and carry a positive perception of the value of data-driven decision-making under uncertainty.

6.2.2. Predicting Events and Outcomes

All the respondents interviewed for this study perceived data-driven decision-making as useful in forecasting and predicting of events under uncertainty. The results also indicated that only one of the respondents, a member of the EXCO and Portfolio Manager in financial services, used data to confirm occurrence of risks previously forecasted as possible. When the data captured from respondents was further analysed, 'predictive capability' and 'power of data use' co-occurred in 15 of the 341 first order codes. Co-occurrence reveals the extent of thematic overlap signalling relationship between concepts that should be explored further (Macia, 2015)

This result highlights the consensus among respondents on the role of data-driven decision-making to help predict potential outcomes under uncertainty. This is a particularly valuable outcome as it corroborates the value of data within uncertainty versus certain environments simplified as scenarios of unknown unknowns and known knowns respectively (Gigerenzer & Gaissmaier, 2011; Baltussen, van Bekkum & van der Grient, 2018).

Moreover, if data is used by South African senior managers for its predictive capability, this finding aligns with the work by McCann (2020) that argues for the use of data to support data-driven decision-making under uncertainty through the use of the Bayesian Updating approach. This approach follows the use of data to enhance the effectiveness of decision. This is particularly valuable in uncertainty, an environment within which a prime characteristic is the inability to effectively and conclusively ***predict*** the outcome of a decision.

6.2.3. Decision Moderator and Advocate for Rationality

Respondents in this study also perceived data-driven decision-making to be a valuable decision moderator under uncertainty as it enforces rationality. Individually, respondents alluded to the power of data in supporting the decision-making process by preventing manipulation and discouraging emotive decisioning. As respondent RM noted:

> *"You set those up when you're not emotional. So, when you walk into the new house and it's got an amazing view, it's got an infinity pool and exciting kitchen finishes, but it costs a lot more money that you wanted it to, or it's in a wrong neighbourhood or whatever the problem is, you go back at your list and say, what was on our list? How does this house stand up to what my list said? And if your list says you shouldn't be buying the house, you don't buy the house."* (RM)

Related literature reviewed in Chapter 2, noted that making rational decisions under uncertainty requires adoption and careful application of a four step process. This starts with identification of historical data the decision maker is faced with, followed by recognition of the cognitive biases that each of the categories trigger (Einhorn, 2020). Furthermore, according to Einhorn (2020), contextual data is known to trigger *framing bias a*nd the above quote from the interviewee makes for a perfect example of this concern

Therefore, this theme and its occurrence amongst South African senior managers, indicates a perception of data-driven decision-making as a plausible approach to maintain objectivity and rationality under uncertainty.

6.2.4. Mindset and Skillset Required

South African senior managers were found to carry a perception that data and access thereto requires analytic skills to extract value even though only one respondent had direct daily interaction with big data analytics, big data analytic capabilities and decision-making tasks. Pigni, Piccoli and Watson (2016) found that big data analytic capabilities a prerequisite for organisations to derive value from big data technologies and investments.

The authors further noted that the "ability" described in big data capabilities coalesces in four dimensions namely (1) mindset; (2) skillset; (3) dataset; and (4) toolset (Pigni et al., 2016). A similar view is that of Ransbotham et. al (2016) who concluded that it is imperative that the analytics be able to provide meaningful insights for managers and decision makers to obtain any value from big data.

Respondents who did not have daily interaction with big data but still advocated its value, were employed in organisations that have made sufficient provision of resources, internally or externally, to provide this function and/or the actual relevant data and insights thereof for data-driven decision-making. This is a corroboration of the *mindset* ability to big analytic capabilities (Pigni et al., 2016). Mindset in this context is explained as the organisation's willingness to invest in data-driven initiatives bearing in mind the risk this may come with. This mindset comes about as an appreciation for the value digital data streams (DDS) to influence a change in organizational culture that encourages and promotes data-driven decision making.

This finding from the interviews, shows convergence of theory and practice, as encountered by managers in the South African context, both at an individual and organisational level.

6.2.5. Toolset and Dataset Required

The final theme emanating from the data related to Research Question One, was the perception of data being essential to supporting decision making processes. However, a number of respondents experienced the data as not being used effectively under uncertainty.

Pigni et al. (2016) explained toolset and dataset as abilities with which organisations need to position themselves to derive value from big data. The authors define dataset as the "capacity to effectively identify, intercept, and access real-time data streams that match organizational needs for value creation" (Pigni et al., 2016, p. 20) with toolset being the infrastructure made up of hardware and software.

It is therefore important to note that the experiences of South African senior managers, currently shows a deviation from the recommended setting for the derivation of value from big data. Optimal conditions are understood as "not merely a problem of having the right "ingredients" – the right stuff – but instead demands astute management of their systematic interaction in an organizational setting" (Pigni et al., 2016, p. 18).

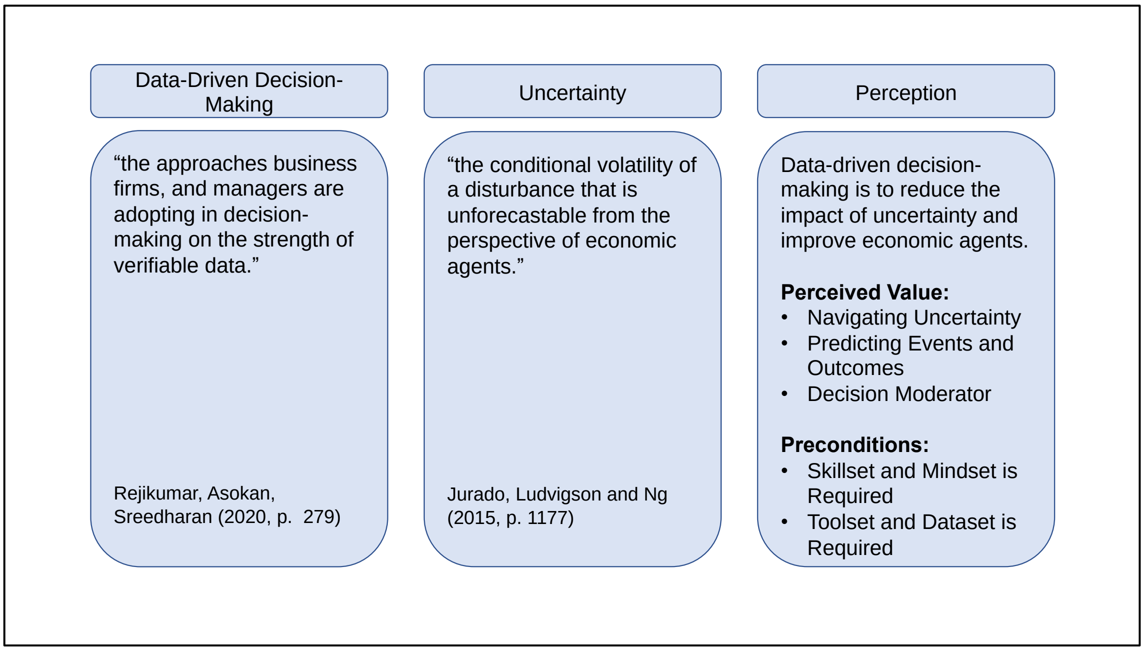

Figure 7: Perception of data-driven decision making under uncertainty

Source: Author

6.2.6. Conclusion

The question of how South African senior managers perceive data-driven decision-making under uncertainty was explored through the themes outlined. The principal findings of this question revealed an insight regarding uncertainty reduction and/or avoidance.

6.3. Discussion of Results for Research Question Two

Use of Big data and Big Data Analytics used for Decision-Making under Uncertainty

Building on from the perception on the use of data to support the decision-making process explored in research question one, respondents were then asked to detail how and when they used and relied on data to support the decisioning processes they oversee. As a first outcome, the majority of respondents expressed that data-driven decision-making under uncertainty is largely directed towards strategic decisioning.

Theory has shown that "bad events often seem to increase uncertainty, events like oil-price shocks, terrorist attacks, and wars" (Bloom, 2014, p. 161). In the case of 2020, the global COVID-19 pandemic is certainly a bad event that has increased uncertainty. One of the results of this uncertainty in South Africa has been the 51% contraction of the economy (Stats SA, 2020c). What is also known, from literature, is that the primary distinction between uncertainty versus certain environments is simplified as scenarios of unknown unknowns and known knowns respectively (Gigerenzer & Gaissmaier, 2011; Baltussen, van Bekkum & van der Grient, 2018). Furthermore, one characteristic of complex environments is unknown unknowns (Snowden & Boone, 2007), to which we can infer that uncertainty is indeed a form of complexity. The decision-making framework in complexity, recommends that decision-makers ought to *probe*, *sense* and *respond* (Snowden & Boone, 2007). It is also interesting to note that Alexander et al. (2018) adapted this recommendation into what is known as the Cynefin framework, referenced in Chapter 2 of this report, that links strategic decisions to complex conditions.

It emerged from the results discussed in Chapter 5 that a majority of respondents referred to the use of data-driven decision-making as predominantly for strategic decisions. One other respondent, a portfolio executive, primarily used data-driven decision-making for risk mitigation, an uncertainty impact avoidance and/or reduction application. Prevalence of strategic decisions was noted in the experiences of those decision makers who are in management consulting roles discharging an advisory function. A quote of this from the interviews describes lived experience:

> “We normally do what you call *asset and liability modelling*, that we do, and in most cases, it informs those people who are going to actually be investing money. Imagine in a period of *high uncertainty*, sometimes you’ve got *incomplete information*, but you just have got indications that… I mean, I think we’re thinking that the market is going to go this way, so as an organisation, or *as an advisor*, you need now to say, okay, I think because of this, maybe you can go on to make this decision.” (RL)

Indeed, South African senior managers have adopted data-driven decision-making for strategic decisions and navigate uncertainty, however. Other respondents have expressed the use of data-driven decision-making in uncertainty for tactical and operational decisions, even in times of uncertainty. Despite data-driven decision-making being dominant for strategic decisions, it is an interesting to note that the use of data-driven decision-making has already extended to other decision types, potentially fuelled by anticipated effects of the Fourth Industrial Revolution (World Economic Forum, 2016).

A second angle to this research question was to explore when reliance is placed on data to support the decision-making process. Key findings from the research are expressed in Chapter 5 with the emergent theme being credibility of data as the determinant for decision makers placing reliance on data. Respondents were unanimous in highlighting the use of a combination of both internally and externally generated data. The one flaw found in external data is relevance. To this point, two respondents detailed a role for a process of triangulation, the same was implied by other respondents. This further cemented the need to recognise that credibility is a major determinant for data reliance.

Theory detailed in Chapter 2 introduced the veracity of data as the fourth attribute; a component of the 4Vs definition of big data (Goes (2014). The definition of veracity in the study by Goes (2014) is the quality of data. Relatedly, Janssen et al. (2017) address the issue as completeness, consistency and accuracy, aspects echoed by respondents in this study. The data from this study underscored that data quality is an enduring concern for senior managers in South Africa firms. Irrespective of any impact of low or high intensity of uncertainty, such as that related to Covid-19; data quality has been a long-standing challenge. Improvement in the quality of data could yield direct effects through enhanced quality of decisions. A respondent from management consulting industry lamented experiences with significant data quality and redundancy challenges in clients dated legacy systems.

6.3.1. Conclusion

The purpose of this question was to explore *how* and *when* South African senior managers used and relied on data for data-driven decision-making. It was inferred from literature that data is useful in the *probe, sense* and *respond* process for strategic decisioning in complex environments, characterised by uncertainty (Snowden & Boone, 2007; Alexander et al., 2018). It can also be concluded that South African senior managers understand the prerequisites for data-driven decision-making, one of them being data quality and credibility (Goes, 2014; Janssen et al., 2017). Figure 9 below illustrates how South African senior manager's understand data-driven decision-making under uncertainty.

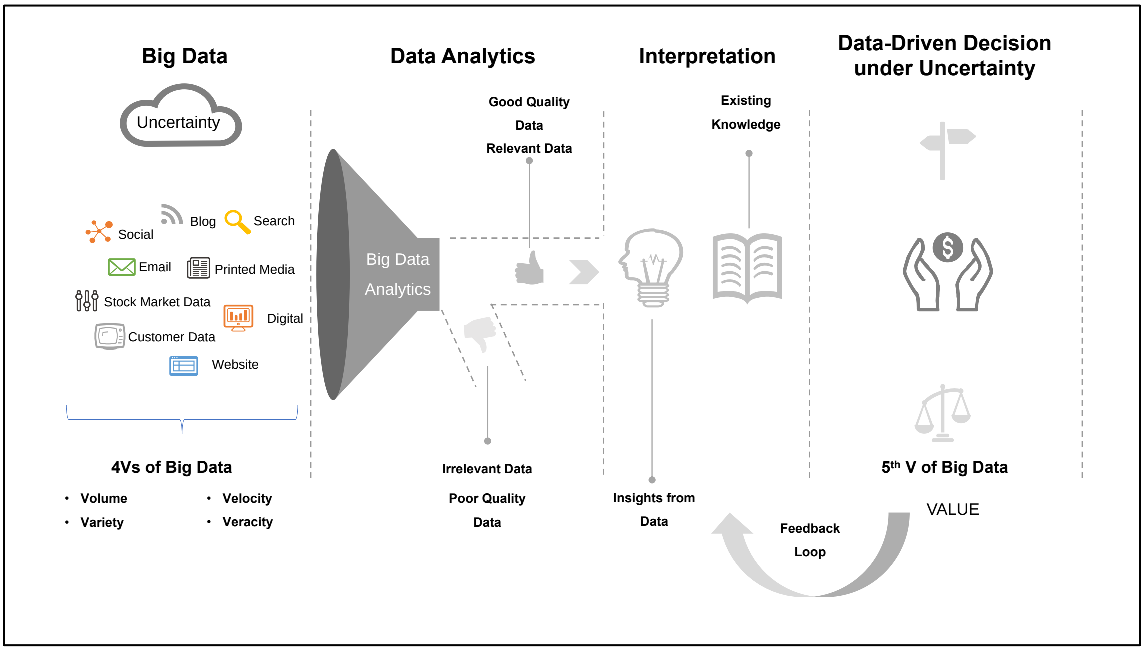

Figure 8: How and when data-driven decisioning is used under uncertainty

Source: Author

The model shows how and when data is used to support the decision-making process. It points specifically to the importance of relevant data and not to accept all data that comes through the various data collection tools a business invests in. Moreover, it is the relevant data that is paired with existing knowledge to provide a base for critical analysis of decision options to arrive at a decision. The feedback loop in the far right of the model that indicates how the value of big data is realised, from which these specific insights become the existing knowledge for different types of decisions in the future.

6.4. Discussion of Results for Research Question Three

Challenges or obstacles to data-driven decision-making under uncertainty

This question explored the challenges and impediments to data-driven decision-making under uncertainty in a South African context. The challenges were summarised in Chapter 5 and are repeated here for ease of reference.

Table 9: Challenges of data-driven decision making under uncertainty

No.	Challenge Experienced	Theme
1.	Organisational cultures and politics results in reluctance to share useful data across functions or departments.	Sharing of data
2.	Generally, even more so under uncertainty, data obtained is subject to interpretation and may result in differing and/or conflicting decisions taken.	Interpretation of data
3.	Generally, even more so under uncertainty, data collected needs to be relevant for it be useful.	Relevance of data
4.	Under uncertainty, data often comes in sporadically and only gives a “piece of the whole picture” and may lead to incorrect decisions made.	Real-time data
5.	Under uncertainty, there is often inconsistencies in quality and credibility of data, sometimes due to manipulation or human intervention.	Quality and credibility of data
6.	Under uncertainty, insufficient, relevant information introduces a need for human intervention which brings an element of bias.	Objectivity of data
7.	Under uncertainty, change is rapid and real-time data is seemingly lagging behind to offer value in timely data-driven decisions.	Real-time data
8.	Generally, [big] data comes in large volumes that are raw, is expensive to collect and/or obtain and “sanitize” for good use.	Interpretation of data
9.	Under uncertainty, the trends take time to emerge and therefore, adds to the difficulty in calculating probabilities on the [uncertain] future.	Prediction through data
10.	Generally, most organisations and/or South African senior managers do not possess the skills to collect and make effective use of [big] data.	Skills for data usage

Whilst challenges have been adequately documented in literature and other studies, the level of preparedness for the Fourth Industrial Revolution (World Economic Forum, 2016) within the South African market coupled with the impact of the global COVID-19 pandemic on South Africa, were the primary motivators for this research question.

6.4.1. Time Delays in Accessing Data

It was noted that the most prevalent amongst the respondents was the timing of data availability. The impact of uncertainty and complexity experienced by respondents has led to convictions over a growing urgency for firms to have *real-time* access to data**.** The urgency for objective data-driven decision-making intensifies under uncertainty. Data that is availed too late exposes the firm to subjectivity and bias in decisioning. As respondent RL pointed out:

> "I think also, the other challenge is, what I've noticed is, *there are companies that do not have the capability to provide real-time data*. So, there is a lag; there is a *time lag*. But if you use that data that you have at your disposal, it can inform you. I mean, it removes also an *element of bias* that also exists, I mean, it's *inherent in us*." (RL)

Insights from literature also underscored concern over the speed at which relevant data is made available as an essential competency for big data analytics and analytic capabilities. The ability to "mine" data at fast speeds and draw insights is the aspect of toolset and dataset described by Pigni et al. (2016). Toolset and dataset refer to the ability for an organisation to position itself to derive value from big data. Specifically looking at dataset, this is the "capacity to effectively identify, intercept, and access real-time data streams that match organizational needs for value creation" (Pigni et al., 2016, p. 20), supported by the infrastructure being hardware and software, referred to as the toolset.

6.4.2. Subjective interpretation

A second aspect of concern highlighted by the primary data pertained to subjectivity of interpretation. Whilst this challenge flowed from the respondents, the researcher found this to be contradictory to earlier insights drawn from interviews by other respondents. The majority of the respondents perceived that data-driven decision-making as an advocate for rationality in uncertainty and an appropriate decision moderator to a degree. This is due to one of the inherent characteristics of data, that it is objective. Respondents who cited this as a challenge inferred that data obtained should be the answer to a decision point, which is only plausible in computational decisions. For decisions requiring application of existing knowledge and marrying this with existing knowledge requires decision-makers to have appropriate decision-making skills and experience; see Figure 1 in Chapter 2.

The researcher, therefore, concludes that there may be a misunderstanding of the role of data-driven decision-making under uncertainty. To further corroborate this assertion, literature reviewed in Chapter 2 suggested that data-driven decision-making came about as a result of the incorrect perception that management was an art as opposed to a science, resulting in managerial complacency (Rejikumar et. al, 2020). This complacency fuels the misunderstanding of the role of data-driven decision-making due to managers being comfortable with making decisions intuitively and not using *insights* from data for cognitive application in decision-making.

6.4.3. Delayed Relevance of Data Trends

One challenge of data-driven decision-making expressed by one respondent in the investment and asset management industry was that of the data coming in chunks and not showing the full picture at a time. This experience was corroborated by another respondent, engaged in enterprise risk management as an actuary, who expressed that recurring events take a considerable period of time to be regarded as a trend. This challenge, particularly resonated with another respondent who highlighted the rate of change under uncertainty and this rendered probability modelling extremely difficult.

> "If you pick long-term macro trends, those sorts of things have momentum behind them, and *macro trends don't change quickly*; so, we don't need to be highly accurate to be successful long-term. The problem is data comes in *sporadically* and it comes in large quantities and it's very difficult to *marry everything together* so that you've got a *timeous big picture* of who or what's going on." (RM)

Data quality and relevance as another suite of challenge resonated with seven respondents, who all highlighted that data accuracy, integrity and completeness affect data-driven decision-making under uncertainty. Closely related, is the attribute of data being comprehensible, relevant and readable. This was also found to be an interesting finding as it was quite contrary to the expected value of big data, big data analytics and big data analytics capabilities espoused in literature (Timmerman & Bronselaer, 2019).

6.4.4. Human Intervention and Manipulation of Data

The quality and relevance challenges were mostly attributed to data manipulation due to human intervention. The aspect of human intervention during data analysis is argued to bring in an element of bias and subjectivity. Two respondents who are in the information technology function of their respective organisations, believed that human intervention is linked to disparate systems that cause complexity in data and data management processes. This view was further corroborated by two other respondents, RL and RMk, who both expressed that a majority of the challenges with data are due to poor data management processes, to which businesses lack augmented, synergy and integration of the systems and processes within organisations. This finding cement existing literature, to the extent that data quality is compromised further in uncertainty (Timmerman & Bronselaer, 2019). This challenge, however, can reduced by employing appropriate data analytic technologies to decompose the complex predicate uncertainty in data to simpler and easily verifiable ones in simpler Boolean rules (Timmerman & Bronselaer, 2019). It would suggest that South African organisations have not factored in the reduction of uncertainty in their big data collection and analytic technologies.

6.4.5. Data Sharing Culture

Another respondent identified a data-sharing culture as an obstacle to data-driven decision-making under uncertainty. This culture of not sharing data may be specific to the management consulting industry, as the same sentiments were echoed by another respondent who is a consultant at another consulting firm. This may be inspired by the fierce rivalry amongst consulting firms, particularly for market share and customer retention. Eggers (2013, p. 19) makes the assertion that *"data as the new currency"*. Expanding interaction and transactions on the widening footprint of digital platforms has accelerated growth in value of data. Whilst data is the new currency (for competitive advantage), this finding is a theme corroborated by Davenport and Bean (2018), who explain that whilst most organisations have embraced analytics, they have not embraced a data-driven culture, and this may explain the reluctance to share data amongst colleagues within the same organisation.

6.4.6. Impact of Legislation

Legislation surfaced as a rising source of challenging complexity for data management processes and data-driven decision-making The Protection of Personal Information (PoPI) Act 4 of 2013 implemented in South Africa was cited as one of the major challenges and inhibitors of data and information sharing. Respondents from information technology sector were close to the detail of what goes on with data and data analytics.

6.4.7. Acute Shortage of Relevant Skills

Another challenge emanating from the interviews, is that of the global shortage and in particular, the high mobility of data analytics skills in South Africa (Kozyrkov, 2018). One respondent specifically cited this as a major challenge in their organisation, that has geographical presence in most of Africa, Asia and Europe. This finding is strongly corroborated by literature outlined in Chapter 2, in particular, Nakagwa (2020), who's study can be used to explain what have been found to be low frictional costs of data analysts and/or data scientist skills transfer and migration. An extract of her lived experience from the interview is as follows:

> "We train people, *we upskill them and then they get hired, they get scooped by companies in Italy or maybe in America* you know? So that is one of the big problems." (RT)

The high demand and inability to meet global competitive remuneration rates by South Africa has resulted in failure retention of such skills in South African organisations (Nakagwa, 2020).

6.4.8. Ease of Access to Data

Ease of access to data was a challenge of data-driven decision-making under uncertainty that trended amongst respondents. According to Lipshitz et al. (1997), first step to decisioning under uncertainty is performing a rigorous information search to reduce uncertainty. This process is further corroborated by Einhorn (2020), who details a four-step process that starts with an in-depth analysis of data at the decision-maker's disposal, mostly aimed at identifying and overcoming biases that these data trigger.

However, findings point to a difficulty in accessing data among South African senior managers. One respondent highlighted that a decision maker is more likely to default to set biases and heuristics (Mousavi & Gigerenzer, 2014) when data access is a challenge.

> "Yes, and then it is *always easy to default to what you are used to if the new or the different is not as easily accessible nor understandable* and I also think demystifying or deconstructing the notion of complexity of data." (RMa)

The data access challenge was echoed by another respondent who experienced one of the major challenges of data as being access and that there could be motivation of segregation of responsibilities within organisations. The respondent and several others highlighted the number of enablers they had to go through to access the desired data for decision-making. Perhaps this adds to the challenge of data not being available in real-time as a major challenge under uncertainty. Moreover, traditional custodianship of data management processes to the information technology (IT) department, must evolve given the ubiquitous access to data now required for decisioning.

> "Because I found that *IT tends to prioritise technology*, *they are not thinking about the business need, what my needs are, and how this is going to make my job or improve my decisions and priorities*, and exactly what you said earlier on, the scenarios, what can I do out of this data capabilities. *But often in some organisations that entire capability sits with IT*, and it almost feel like you are knocking at the door of IT to help you give you your data so I can make my decisions. *I think that needs to be like if you move it away from IT, IT is a technology enabler, and not the owner of data analytics.*" (RT)

The lack of clarity of the mandate for departments within an organisation is one of the reasons for the failure in strategy implementation, for example, the specialist culture and difficulty links tests (Goold & Campbell, 2002). Segregation of responsibilities is now an essential component of a data-driven culture and strategy within an organisation. This aligns with views by Sull, Homkes and Sull (2015), who highlight one of the flaws of strategy execution by management as believing that communication is equivalent to understanding. In their study, Sull et al. (2015) describe a situation in which executives fail to formulate and execute a, the context of this research, *digital* strategy, as devastating. The lack of direction and clarity of mandate within organisational structures to an extent that it stifles digital strategies gives nuances that the c-suite of the organisation does not fully comprehend the objective of the formulated strategy.

6.4.9. Conclusion

The lived experience of the respondents highlighted challenges imposed by (1) timing and speed of data delivery; (2) data quality and (3) insights on aspirations to establish data driven decision making. At the core of these seems to be inadequate big data and big data technology investment. Pigni et al. (2016) advanced the notion of a right combination of conditions to enable a data driven culture to take root. The authors point out that it is “not merely a problem of having the right “ingredients” – the right stuff – but instead demands astute management of their systematic interaction in an organizational setting” (Pigni et al., 2016, p. 18).

6.5. Discussion of Results for Research Question Four

Conditions that Encourage the use of Data-Driven Decision-Making under Uncertainty

This question examined the conditions and/or enablers of data-driven decision-making under conditions of uncertainty. This line of investigation was central to the objectives of the research. Mikalef et al. (2020), highlighted the gap in understanding of the conditions that should be prevalent, if at all, for big data and big data analytic technologies to yield competitive gains. Respondents' contributions were examined and consolidated into a summary view as presented in Table 7 in Chapter 5. It was interesting to note that most respondents surfaced an array of factors that complemented a central need for increased investment in big data analytics and big data analytics technology.

6.5.1. Data Ecosystems

Adequate and appropriate investment in big data technologies was the most common condition that could enhance the use of big data. Several respondents believed their organisations had not done enough to ensure the right infrastructure was deployed to optimise the power of data-driven decision-making under uncertainty. With respect to increased investment, the findings underscored the need for an ecosystem of both internal and external capabilities as a key condition to enhancing and encouraging the use of data to support the decision-making process. Moreover, a redesign of management information systems (MIS) to make them more integrated is required. This is set to encourage omnipresent data interaction across the organisation.

Pigni et al. (2016), discuss a need for organisations to have the toolset. This refers to the technologically based facilities that ought to be powerful enough to influence the organisation's ability to profit from big data. As part of the increased investment towards big data technologies, toolset requires the organisation to employ the tools to help frame decisions and draw full potential of data-driven decision-making. The findings also surfaced the issue of investment into artificial intelligence and machine learning as tools employed to (1) assess relevance of data; (2) recognise trends; and (3) moderate human-led decisioning (World Economic Forum, 2016; Schwab, 2017). It is mentioned in Chapter 2 of this research, that big data analytics (BDA) are the use of clever methods and techniques to extract meaningful information Goes (2014). It is also further explained that specific skills are required to decipher this data into a usable state, and these skills involved the ability to of the firm to capture and analyse data towards generation of insights (Gupta & George, 2016).

6.5.2. Data-Driven Leadership

Leadership as a catalyst to data-driven decision-making under uncertainty emerged as an important aspect. For a start, establishment of EXCO level roles such as a Chief Information Officer are key appointments that could foster and encourage data-driven decision-making. The mandates of these appointments would be primarily to drive a data-driven culture (Christensen, 2006) within the organisation. Supportive executive behaviours that prioritise the use of data, encourage its use across the organisation.

It also emerged that there is growing belief that raising staff awareness of the personal benefits of data can motivate employees into adopting the culture to see those benefits in their roles. Respondent RT specifically made an example of using data in the morning to gauge the level of traffic congestion on the roads. This direct personal benefit to a user of data has spill over effects raising consciousness of the benefits data making adoption in the workplace more seamless. Continuous professional development and refresher training of analytic skills were also highlighted to encourage the use of data.

Specific to those in financial services, the issue of sound data governance was viewed as a condition that could encourage data-driven decision making. Data governance, explained as the harmonisation of data processes within an organisation, augmented various sources to make data richer and more accurate Similarly, decision-making processes ensure value is extracted. As respondent RMk noted:

> "...*augmentation and consolidation of various sources* so that you have a true picture, and an *accurate picture for that matter*, which is quite critical…." (RMk)

In harmonising processes and governance, there may be need to restructure the mandate of the IT department encouraging the use of data. The respondent highlighted the disconnect from business processes that lies within the unclear custodianship of data, and that a restructure to have the IT department be in charge of technological infrastructure and analytical capabilities with the user of the data would encourage data-driven decision-making under uncertainty.

> "I think that needs to be like if you move it [data analytic capabilities] away from IT, *IT* [department] *is a technology enabler*, and not the owner of data analytics. The *data owners must drive all initiatives associated with the improvement of data analytics*…." (RT)

Furthermore, it emerged that respondents believe that leadership to address uncertainty is a key ingredient to driving and encouraging data-driven decision-making in uncertainty. Literature explains that a systems thinking and learning mindset can enable performance in uncertainty (King & Badham, 2019). It can be inferred that such leadership approaches *enable* clarity within an organisation, holistically viewing data as part of the whole and not a practice isolated to one department. This view is similar to Uhl-Bien and Arena (2017) who found that in complexity, *emergence*, being the creation of new order in a networked system to foster change, is required to counter complexity. This is done through people, technology, information and resources and therefore, "leaders enable adaptive responses by engaging in and creating conditions that feed and fuel emergence" (Uhl-Bien & Arena, 2017, p. 11). Several respondents believed that it was imperative to (1) keep data processes simple; and (2) analyse and focus on value-adding processes.

6.5.3. Uncertainty and Complexity

According to Millar et al. (2018), innovation as a driver of and outcome of uncertainty. The theory put forward above, suggests that data-driven decision-making can be conceptualised as innovation in decision-making, given that seven out of 10 respondents experienced an enhanced use of data for decision making since the onslaught of the pandemic.

Motivating factors for this included a need to (1) navigate uncertainty; (2) predict events and outcomes; (3) provide the necessary skillset and mindset required; along with the (4) toolset and dataset required. All these drivers feed into the overall themes identified in the findings of this study. The themes were that data-driven decision-making under uncertainty firstly provides an objective measurement instrument (for decision under uncertainty.

Secondly, it is a compass and guide for navigating unknown outcomes characteristic of uncertainty. Third, data driven insights and decisions are a strategic tool for developing new opportunities; whilst simultaneously, as a fourth outcome, serving as a tactical tool for defending existing market share. The findings lead to infer these as empirical aspects of the clarity sought by Mikalef et al. (2020), when they suggested the needs for further exploration into conditions, that must be fostered for organisations to achieve value from big data technologies to serve managers dealing with uncertainty, an aspect of complexity.

6.5.4. Conclusion

In conclusion, it emerged that the conditions that could encourage the use of data-driven decision-making under uncertainty are a combination of both tangible and intangible factors. The respondents highlighted the need for more attention to be given to big data and big data technology investments. Further, these investments ought to be geared towards creating data ecosystems, to make data sharing more ubiquitous within an organisation. Greater emphasis should, however, be directed towards the intangible and somewhat, “softer” enablers. These include leadership, geared towards enabling change and adaptability in uncertainty. The leadership required to address uncertainty; aimed enabling performance in VUCA environments (Horney et al., 2010), and this leadership bears the attributes of “systems thinking, tolerance of ambiguity, ability to handle paradox, distress tolerance and learning mindsets” (King & Badham, 2019, p. 3).

This malleability ought to be fostered in decision-makers by raising awareness of the value of data-driven decision-making through training and continuous development for critical skills. Relatedly, sound governance around data and data processes as well as a culture that supports data-driven decisioning through suitable and appropriate appointments in the executive structures plays an important role. A striking enabler was uncertainty and complexity in its very nature. Given what we know from literature, combined with the empirical findings from this study, uncertainty appears to have been a catalyst for data-driven decision-making in uncertainty.

The last section of this chapter cements these views through the impact and benefits respondents experienced in their application of data-driven decision-making under uncertainty.

6.6. Discussion of Results for Research Question Five

Benefits of data-driven decision-making under uncertainty.

The question was primarily aimed at understanding and exploring the benefits of data-driven decision making under uncertainty. Some of the benefits were supportive of current literature that endorses data-driven decision-making as a source of value for organisations, current discourse being that of McCann (2020) who highlights the use of Bayesian Updating to enhance the accuracy of information for decision-making. Chapter 1 described an opportunity for contribution by this study, by giving insight into the benefits of data-driven decision-making under **uncertainty**. Relevant themes, that emerged from the empirical data captured by this study to explain the benefits of data-driven decision-making under uncertainty are detailed below.

6.6.1. Objective Measurement Instrument

Uncertainty in its very nature, presents a series of unknown unknowns due to insufficient information to predict likely outcomes of decisions taken (Gigerenzer & Gaissmaier, 2011; Baltussen, van Bekkum & van der Grient, 2018). Due to this characteristic, the interpretation of events and occurrences becomes highly subjective; the benefit that data provides when faced with such uncertainty, is objectivity. Factual data when carefully sourced, provides a valuable reference point in the height of uncertainty that can silence the noise and bias that may emerge from decision-maker backgrounds and heuristic (Mousavi & Gigerenzer, 2014) influences. This is was clearly articulated by respondent RB

> "I think the *benefits are definitely that its objective decision-making* that's taking place. It's very difficult for *people to drive agendas and for people to manipulate decision-making processes or decision-making*, if the data says other words." (RB)

6.6.2. Guiding Compass in the "Eye of a Storm"

When organisations are confronted with uncertainty, they can be likened to being in the eye of a storm. Lipshitz et al. (1997) explains the first step of the R.Q.P. heuristic as that or reducing uncertainty by rigorously looking for information to quantify uncertainty. A more recent study by Einhorn (2020) presents a four-step process to make rational decisions under uncertainty that corroborates Lipshitz et al. (1997). The research gap in both these studies is the lack of clarity on *how* or *what* techniques would prove to be valuable to reduce uncertainty and/or improve decision maker rationality. This aspect was a focus of interest for this study.

This research question led to a focus on how decision makers reduce uncertainty and simultaneously improve rationality under uncertainty. Data-driven decision-making, in the experiences of the respondents, is a means by which this can be achieved thus providing the "compass" needed to navigate the uncertainty, that may be unprecedented, as is the example of COVID-19. McCann (2020) explains the power of Bayesian Updating as a means of improving probability modelling, which could prove powerful to decision makers embarking on scenario planning and strategic foresight initiatives.

6.6.3. Offense v. Defence

The research has led to identification of data-driven decision-making under uncertainty as an effective *offensive* tactic through which organisations identify and develop new opportunities for growth. According to Artinger et al. (2014) uncertainty can be a driver of innovation resulting in new products. In the fierce fight for survival under uncertainty, strategic decisions that foster deeper attention to customer behavioural economics and markets, through the effective use of data has led to competitive gains for organisations. As one respondent testified, such innovation spurs the development of new market or product strategies:

> "Ja, I suppose the proof is in the pudding hey? So, like I said, we started a *billion Rand* turnover organisation last year, pre COVID, *so we are the biggest debt collector in SA*, so I mean it is the *technology led and data analytics driven* heart of the organisation that helped us to get where we are." (RSt)

The *defensive* benefit of data-driven decision-making under uncertainty is in relation to protection of market share and/or financial position. Data allows for insights to be drawn that enable organisations to manage risk inherent in all decisions taken under uncertainty.

6.6.4. Conclusion

The research question has led to important insights around the benefits of data-driven decision-making under uncertainty. Perhaps one of the important insights is the role of data-driven decision making towards encouraging rationality in decision-making. What was already known from literature is that rationality is required in uncertainty (Einhorn, 2020) but what was under developed in its exploration was insight into the tools and techniques that a decision maker could adopt to encourage rationality. Amongst the key insights, are the defensive and offensive benefits of data-driven decision-making under uncertainty. These serve as catalysts for growth as well as valuable artillery for protection of market share.

Figure 10 below is a pictorial illustration of the benefits of data-driven decision making under uncertainty. The figure has been based on the *infinity* symbol, to highlight the continuous interaction of the benefits as the decision-maker engages data-driven decision-making under uncertainty.

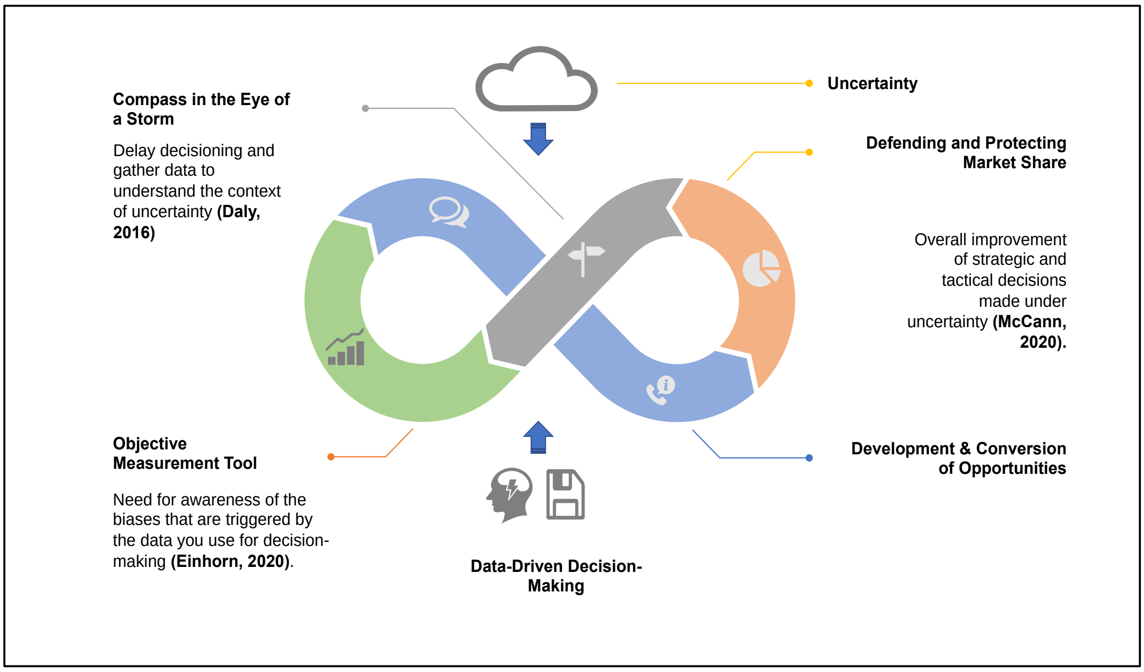

Figure 9: Benefits of data-driven decision making under uncertainty

Source: Author

6.7. Conclusion

In conclusion, the research has led to important insights around the benefits of data-driven decision-making under uncertainty. Perhaps one of the important insights is the role of data-driven decision making towards encouraging rationality in decision-making. What was already known from current literature is that rationality is required in uncertainty (Einhorn, 2020) but what was missing in current literature is the practical tools and techniques that a decision maker could adopt to encourage rationality. Amongst the key insights, is the defensive and offensive benefit of data-driven decision-making under uncertainty, most espoused in this being a growth catalyst and also valuable in protection of market share.

7. Conclusion

7.1. Introduction

This chapter concludes this research by consolidating and linking the research purpose to the principal findings, with specific focus on addressing the theoretical outcomes. The discussion also pursues implications for management to address business needs. Some limitations of this study are presented, before recommendations for future research, are outlined.

7.2. Principal Findings

The purpose of this study was to explore the role of data-driven decision-making under uncertainty. It was noted in Section 2.5 that there are significant benefits of data-driven decision-making as highlighted through work done by Brynjolfsson and McElheran (2016b). These benefits primarily manifest as improved firm performance. The scholars emphasised that this was more prevalent and pronounced in organisations that made changes in their management practices (Brynjolfsson et al., 2016b). It was also noted that big data analytics and analytic capabilities had been identified as a common path to growth for most organisations (Kiron, Prentice and Ferguson, 2014). However, it emerged that the uptake in big data analytics and analytic capabilities has seen the anticipated growth and value diminish over time. Mikalef et al. (2020), point to the need to examine the conditions necessary for big data and big data analytics capabilities to lead to competitive gains.

In addition, fortuitously, the unprecedent conditions created by the global COVID-19 pandemic presented ideal context to explore the role of data-driven decision-making under uncertainty. A qualitative research design strategy implemented using semi-structured interviews with purposively selected respondents served to capture explorative insights from senior managers in a diversity of South African firms.

7.2.1. Adoption of Data-Driven Decision-Making under Uncertainty

The study found that data-driven decision-making that is positively perceived by decision-makers under uncertainty leads to widespread adoption of data-driven decision-making under uncertainty. This adoption by decision makers is driven by four themes that emanated from the data analysis as presented in Chapter 5. These themes explain perception of data-driven decision-making under uncertainty as; (1) useful to navigate uncertainty; (2) useful to predict events and outcomes under uncertainty; *but* (3) requires the right skillset and mindset; as well as (4) requires the appropriate and adequate toolset and dataset for organisations to realise value.

The illustration provides a guide for other South African senior managers on what preconditions are required for value to be captured when making data informed decisions.

7.2.2. Data-Led Decisions Types under Uncertainty

The research found that whilst literature highlights a flattening of the curve of competitive and economic gains owing to big data and big data technologies (Kiron et al., 2014) this has changed under uncertainty. The data revealed that some entities in South Africa have grown exponentially in market share and market capitalisation despite prevailing uncertainty, largely owing to harnessing the power of big data and big data analytics.

It also emerged that whilst literature states that uncertainty and complexity calls for strategic decision-making, data-driven decision-making can be applied, successfully and yielding benefits, in *operational* and *tactical* decisioning. The model shows that *operational*, *tactical* and *strategic* decisions taken by senior managers are also guided by data perhaps owing to the Fourth Industrial Revolution (World Economic Forum; Schwab, 2017). Further to what has been explained in Chapter 2, Klaus Schwab, contrasts the decision-making in the Second Industrial Revolution to #4IR as due to the multi-faceted application of technology and the pace of change. The researcher, therefore, finds it plausible, supported by findings of this research, that the varied application of the integrated digital technologies in #4IR allow for *multi-faceted, data-led, decisions types under uncertainty*.

Whilst the value of big data and big data analytic capabilities was found to have been diminishing by Kiron et al. (2014), later research by Ransbotham and Kiron (2017) found that analytics were increasingly becoming a source of business innovation. Potentially owing to uncertainty and complexity, Figure 11 below highlights the perception of data-driven decision-making under uncertainty, highlighting the increased motivation for use under uncertainty multiple decision needs ranging from strategic to tactical.

7.2.3. Application of Data-Driven Decision-Making under Uncertainty

Exploration of the preconditions for data-driven decision-making revealed the importance of data quality, relevance and integrity. It emerged that South African managers have not yet fully understood the interaction of resources (tangible and intangible) and management practices in applying data-driven decision-making under uncertainty. Pigni et al. (2016) explain that value of data-driven decisioning lies in sound management practices of data ensuring use of the right quality and relevance to an organisation.

Amongst the principal findings, it emerged that big data technologies and skills levels in South Africa are not yet geared to handle the pace of change in uncertainty. Amongst other factors, financial resource limitations and the brain drain effect (Biene, Docquier & Rapoport, 2001) stood out as main causes for capability weaknesses. Moreover, South Africa has a culture of not sharing data. Coupled with ineffective c-suite, organisational structures that do not support data-driven initiatives are additional detractors. There are, however, instances where advancements have been made with commensurate evidence in the form of exponential organisational growth.

7.2.4. Conditions for Data-Driven Decision-Making under Uncertainty

The final principal findings emanating from this research, were the conditions for data-driven decision-making under uncertainty. Recent investigations by Mikalef et al. (2020) pointed to a lack of clarity over the conditions that must be prevalent for big data technologies to yield value to organisations in both certain and most important to this research, uncertain environments.

Data ecosystems, comprising of tangible and intangible investments, as well as *data-conscious leadership* were found to be conditions for data-driven decision-making under uncertainty. Importantly, it emerged that *uncertainty and complexity* in its very nature, is a precondition for using data to support the decision-making process that leads to organisational value. These outcomes are presented in Figure 11 as an integrated model for data-driven decision-making under uncertainty.

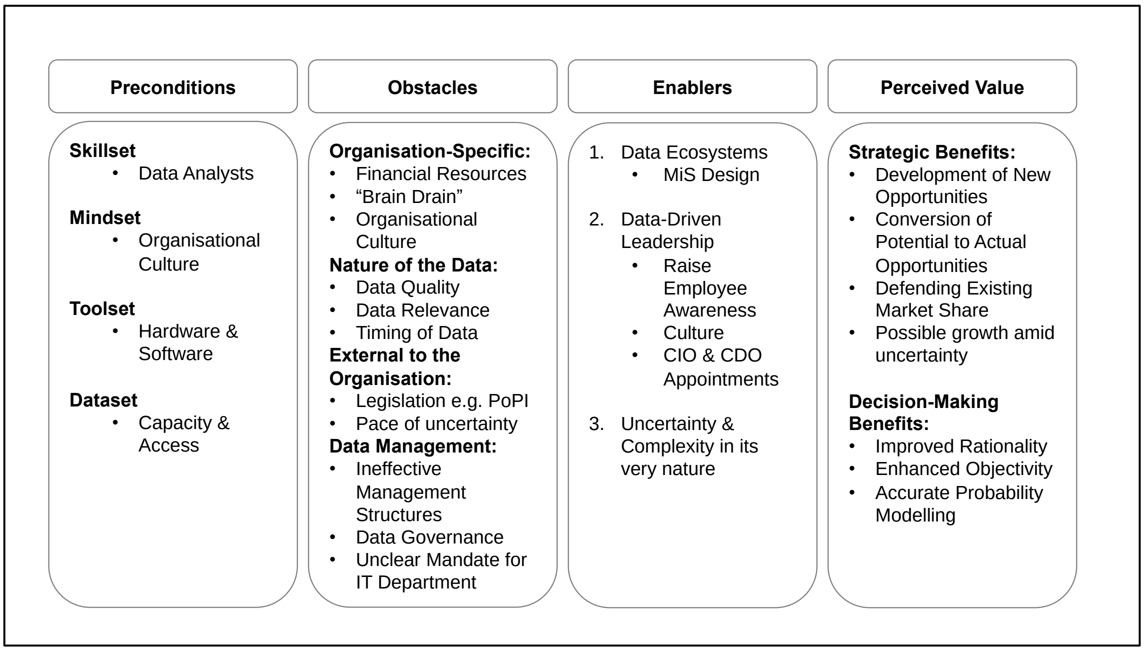

Figure 10: Integrated model for data-driven decision-making under uncertainty

Source: Author

The Research Gap

Prior to this research, it was unclear what conditions needed to be prevalent for big data and big data technologies to lead to competitive gains (Mikalef et al., 2020). Moreover, whilst previous studies showed big data technologies leading to competitive gains (Kiron et al., 2014), it was unclear whether competitive gains could be achieved under uncertainty.

Theoretical Contribution

What is now known, is that data-driven decision-making under uncertainty provides critical survival insights to organisations during periods of uncertainty and necessitates this by enhancing the need for decision maker rationality and objectivity in uncertainty, championed by Einhorn (2020). This research also found that data-driven decision-making reduces uncertainty through better probability modelling advocated for by McCann (2020), subject to specific preconditions for data and data analytics being prevalent. This research has also contributed to our understanding of the enablers that have the capacity to amplify the impact of data-driven-decision-making, leading to exponential growth.

7.3. Implications for Management

In terms of the practical implications, the findings from the research, along with the integrated model can assist South African organisations and management in the following ways:

- The integrated model for data-driven decision-making under uncertainty offers insights into the enablers of data-driven decision-making under uncertainty. This may be used to make strategic decisions more robust and impactful for organisations.

- The integrated model for data-driven decision-making under uncertainty offers awareness of the challenges and obstacles that deter the value of data-driven decision-making under uncertainty. This can forewarn and forearm decision makers to proactively eliminate value deterrents that can hamper effective data-driven decision-making.

- The integrated model for data-driven decision-making under uncertainty offers key considerations for management, specifically around data-driven leadership and organisational culture

- The uncertainty reduction and/or avoidance model for the application of data-driven decision-making by decision type, allows insight and awareness when applying data for various types of decisions being operational, tactical and strategic.

It has, therefore, been established that the integrated model draws insights for decision makers into key considerations and preconditions for data-driven decision-making under uncertainty. The model attends to applications and challenges of the key enablers that make data-driven decision-making effective under uncertainty.

The above implications not only apply to management but to the world of academia as well.

7.4. Limitations

The research has inherent limitations as discussed in Chapter 4.9. As a start, outcomes of qualitative research strategy as employed herein, cannot be extrapolated to a larger population. Moreover, the time horizon of the study was cross sectional in nature aligning with the context of COVID-19 as an example of a period uncertainty. At the conclusion of this study, this uncertainty still prevailed and how long these conditions will last and related effects on data-driven decision-making remain unknown.

Furthermore, the accuracy of the data generated in the interviews may be caused by the interviewer or interviewee's mood on the day of the interview. Any misalignment during this interaction may have direct effect on the quality of the data captured and insight formulated. By virtue of these factors that cannot be calibrated, this presents a credible source of limitation on the research.

Lastly, the use of non-probability sampling, focused on South African senior managers, might have excluded important decision makers from other management levels. The use of data to support the decision-making processes may vary from one level to another, thus giving rise to more or different insights that could be drawn. As partial counteract to this, the researcher did manage to include an executive leadership member in the research sample.

Nonetheless, the research provided important information about the role of data-driven decision-making under uncertainty for South African senior managers, the challenges, enablers and benefits thereof.

7.5. Suggestions for Future Research

Future research can be conducted to further the existing research and deepen understanding of data-driven decision-making under uncertainty. The following are suggested areas of focus along with related rationale:

- A majority of the organisations to which the respondents were employed were predominantly large organisations as per the turnover and employee counts recorded. An extension of this study could be to focus attention on senior managers in small to medium enterprises (SMMEs) who are significant contributors to the South African economy. This community are set to provide insight into data driven decision experiences in firms with smaller resource capacities.

- Research could be conducted to quantify the impact of data-driven decision-making under uncertainty. Scenarios and measures of firm performance would further enhance insight into the effects of data driven decisioning before and after a period of uncertainty.

- Research could be conducted to explore the power of artificial intelligence and decisioning under uncertainty.

- As the study herein sourced data through a cross-sectional format, employing a longitudinal design may provide different insights given that responses will invariably evolve over time.

- Future research could also be conducted to compare the impact of heuristics (Artinger et al., 2014) versus data-driven decision-making under uncertainty on firm performance.

- Future research could test the mediating and moderating effect of certain variables, for example industry culture on the relationship between data-driven decision-making and firm performance under uncertainty.

7.6. Final remarks

The impact of uncertainty is, in most instances, adverse to organisations. Relatedly, what has been experienced in South Africa during the COVID-19 pandemic is negative on both macro- and micro-economic levels.

The findings of this study showed that the role of data-driven decision-making under uncertainty is to improve rationality and enhance objectivity of decision makers. This ultimately improves probability modelling for the decisions made under uncertainty.

This study also found that for data-driven decision-making to be effective under uncertainty, specific preconditions need to be existent, comprising of the right skills, the adequate tools to extract the right data, fostered by a committed mindset and culture to the data-driven decision-making under uncertainty process.

Lastly, this study found that data-driven decision-making under uncertainty is prone to obstacles that organisation-specific, external to the organisation, management quality related and inherent to the nature of data. However, it was found that certain initiatives are recommended to enable data-driven decision-making under uncertainty, and these include creation of data ecosystems and a data-led culture.

This research has the potential to directly and indirectly influence how organisations navigate uncertainty, ultimately providing organisations with essential steps for exponential growth; critical survival insights for some and then opportunities to catapult competitive standing among industry peers. Data provides an objective yardstick for decisioning in uncertainty, a guiding compass to navigate uncertainty and means with which to identify new opportunities whilst protecting the bird in the hand.

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9. Appendices

APPENDIX 1: SEMI-STRUCTURED INTERVIEW SCHEDULE

Name:	Start Time:
Organisation:	End Time:
Job Title:	
Date:	

Thank you for agreeing to this interview, your feedback is valuable, and greatly appreciate you taking the time to provide insights into this research. The title of the research is "Exploring Data-Driven Decision-Making in Uncertainty". During the year of 2020, most of the world suffered the effects of a global pandemic caused by SARS-CoV-2, a virus that causes the disease named COVID-19. This pandemic not only disrupted life as we know it but brought about a significant amount of uncertainty in the business world.

This pandemic, coupled with other experiences have inspired this research, aimed at to exploring and understanding whether data-driven decision-making, as a technique, can be practically applied to offer value to organisations in times of uncertainty as opposed to traditional techniques, supported by research and literature, such as heuristics (Mousavi & Gigerenzer, 2014). The sub-objectives of this study are to:

- Understand the level of knowledge, understanding and perception of, as well as attitudes South Africa senior managers' towards data-driven decision-making in times of uncertainty;
- Determine to what extent South African senior managers use [big] data to make decisions in times of uncertainty;
- Identify the challenges South African senior managers encounter when using [big] data to make decisions;
- Provide the guidance on whether organisations should be placing reliance on [big] data for decision-making for improved performance, protection and/or creation of competitive advantage during periods of uncertainty.

This research and interview are exploratory in nature. With that, I wish to encourage you to speak freely and take comfort in knowing that whilst we will use the information shared in this interview, your identity as the provider of this information, shall remain confidential and anonymous.

You are welcome to withdraw from this interview at any time without prejudice. Please also be advised that we intend on using a third party to transcribe this interview for us and have ensured that confidentiality and anonymity will still be maintained through the use of a Non-Disclosure Agreement for this exercise.

May I kindly ask you to sign this consent form and confirm that you are comfortable with me recording this interview using an audio and/or video recording device.

If you have any concerns, please contact my supervisor or me. Our details are provided below:

	RESEARCHER	**SUPERVISOR**
NAME	Munya Hove	Dr. Charlene Lew
EMAIL	19384239@mygibs.co.za	lewc@gibs.co.za
PHONE	+27 (0) 79 791 9732	+27 (0) 11 771 4284

Signature of Participant: ______________________________

Date: ______________________________

Signature of Researcher: ______________________________

Date: ______________________________

Question 1

To kick-off our discussion, please provide me some information on your organisation and role:

(1) Current roles and responsibilities; (2) Level in the organisation; (3) Company industry/sector; (4) Company age; (5) Size of company – turnover and staff compliment

Setting the Scene:

Uncertainty relates to constant change, hard to predict scenarios, and ambiguous, conflicting, unavailable or unreliable information. In simple terms, these are unknown unknowns.

Question 2

How has COVID-19 contributed to the use of data in your decision-making, if at all?

Question 3

Data-driven decision-making refers to the use of data to support the decision-making process. How and when do you rely on data when making decisions in uncertainty?

Question 4

What sort of challenges or obstacles do you experience when making data-driven decision making in times of uncertainty?

Question 5

Despite the challenges and/or obstacles, have you gained any benefits from using data-driven decision-making as a technique in times of uncertainty?

Question 6

Based on the above, what can be done to enhance the use of data-driven decision making in uncertainty; both at an individual level and organisational level?

APPENDIX 2: CONSISTENCY MATRIX

Research Questions	Literature Review	Data Collection Tool	Analysis
Research Question 1: What are the South African senior managers' perceptions of data-driven decision-making have under uncertainty?	Davenport & Bean (2018), Rejikumar et al. (2020), Daly (2016)	Interview Questions	Content Analysis (coding, categorising and themes)
Research Question 2: How are big data and big data analytics used for decision-making under uncertainty by South African senior managers?	Gupta & George (2016) Pigni et al. (2016), Alexander et al. (2018), Janssen et al. (2017)	Interview Questions	Content Analysis (coding, categorising and themes)
Research Question 3: What are the obstacles and challenges of using data for decision-making under uncertainty?	Goes (2014), Horney et al. (2010), Rejikumar et al. (2020), Nakagwa (2020), Timmerman & Bronselaer (2019)	Interview Questions	Content Analysis (coding, categorising and themes)
Research Question 4: What conditions encourage and enable the use of data-driven decision-making under uncertainty?	Millar et al. (2018), Mikalef et al (2020), Schwab (2017), King & Badham (2019), Christensen (2006), Goold & Campbell (2002), Sull et al. (2015)	Interview Questions	Content Analysis (coding, categorising and themes)
Research Question 5: What is the impact (advantages or disadvantages) of data-driven decision-making under uncertainty?	McCann (2020), Einhorn (2020), Lipshitz & Strauss (1997), Mousavi & Gigerenzer (2014), Artinger et al. (2014)	Interview Questions	Content Analysis (coding, categorising and themes)

APPENDIX 3: FINAL CODE LIST

Advantage of large firms with larger resource pools to activate and manage effective data processes

Advantage of larger firms is their ability to access large pools of data internally

Approach to analysing data_use of historical data to drive forward actions

Approach to managing and analysing data_all reports must have a line of relevance through to EXCO

Approach to managing and analysing data_analysts singularly focussed on the data

Approach to managing and analysing data_building business intelligence (BI)

Approach to managing and analysing data_facilitated by complex systems

Approach to managing and analysing data_facilitated by software

Approach to managing and analysing data_low tech

Approach to managing and analysing data_not all decision makers have access to data management software

Approach to managing and analysing data_software licenses distributed to a select number of users

Approach to managing and analysing data_supported by an internal analytics department

Approach to managing and analysing data_supported by experts external to the organsiation

Approach to sourcing data_semi structured

Barriers to data sharing across firms_a culture of data driven decisioning not yet established across all levels of firms

Barriers to data sharing across firms_housing of data in internal systems

Challenges faced in making decisions during heightened uncertainty_migrating legacy executive behaviours that down play the role of the data in decisioning

Challenges faced in making decisions during heightened uncertainty_only small volumes of data accessible

Challenges faced with covid_diverse trajectory of lived experiences in different countries means data on learnings is not directly transferrable

Challenges faced with covid_maintaining business continuity under changed conditions

Challenges faced with data management activities_data security processes are highly volatile due to security breaches

Challenges faced with data management activities_global shortage of data analysis skills

Challenges faced with data management activities_high mobility of skilled data analysts

Challenges faced with data management activities_Performance management interface can be viewed negatively by staff

Challenges faced with data_becoming progressively more difficult to share due to regulation

Challenges faced with data_blockages in information flow due to reluctance to share

Challenges faced with data_captured but not used effectively

Challenges faced with data_differences in interpretation across individuals and contexts

Challenges faced with data_differences in interpretation across individuals and functions

Challenges faced with data_difficult to assess credibility

Challenges faced with data_difficult to assess relevance

Challenges faced with data_difficult to collect

Challenges faced with data_difficult to interpret into meaningful pictures

Challenges faced with data_difficulties in managing complex data processing systems

Challenges faced with data_human intervention for interpretation introduces bias

Challenges faced with data_impact of negative human behaviours on data processes

Challenges faced with data_impact of pace and level of human understanding on data management processes

Challenges faced with data_inconsistencies in quality and integrity

Challenges faced with data_knowing which data to focus on capturing

Challenges faced with data_lots of unknown aspects

Challenges faced with data_must be packaged into easily understandable messages for different stakeholders

Challenges faced with data_never perfect

Challenges faced with data_risk of overreacting to information outcomes

Challenges faced with data_risk of using partial pictures

Challenges faced with data_sometimes incomplete

Challenges faced with data_supported by disparate systems creating complexity

Challenges faced with data_tends to be captured sporadically

Challenges faced with data_typically comes in large volumes

Challenges faced with data_use of captured data inherently means making future facing decision choices based on information about past occurrences

Challenges faced with data_very expensive to acquire

Challenges faced with data_very expensive to establish necessary technologies to for analytics

Character of uncertainty in business_creates opportunity for large earnings

Character of uncertainty in business_fluctuating consistency in decisioning due to subjectivity

Character of uncertainty in business_increased risk from changed/changing behaviours in clients

Character of uncertainty in business_knowingly relying on marginally reliable data

Character of uncertainty in business_living with the possibility of being wrong about a decision choice

Character of uncertainty in business_operating in the face of unknown outcomes

Character of uncertainty in business_operating in unprecedented conditions

Character of uncertainty in business_volatility demands urgent decisioning

Characteristics and conditions of data_admitted use of lower volumes

Characteristics and conditions of data_blunt to decision specifics

Characteristics and conditions of data_blunt to ethical implications of its objective outcomes

Characteristics and conditions of data_challenging to store

Characteristics and conditions of data_collected at very high speed

Characteristics and conditions of data_governed by POPI regulations making it difficult to share information

Characteristics and conditions of data_has generally become readily available

Characteristics and conditions of data_large volumes required for strong AI algorithms

Characteristics and conditions of data_must be made readily accessible

Characteristics and conditions of data_must be managed for accuracy and integrity

Characteristics and conditions of data_must be readable, understandable & interpretable

Characteristics and conditions of data_often impacted by time delays in yielding fully optimised image of insights

Characteristics and conditions of data_requires cleaning before its usable

Characteristics and conditions of data_requires human intervention to filter for relevance

Characteristics and conditions of data_requires large resources to sources and store

Characteristics and conditions of data_requires large volumes for stronger interpretation

Characteristics and conditions of data_requires some kind of processing to become information

Characteristics and conditions of data_some systems are unable to capture realtime data

Characteristics and conditions of data_takes time to invest and build data capability and infrastructure

Characteristics and conditions of data_typically a record of past activity instances

Characteristics and conditions of data_unable to guide decisioning in evolving unprecedented situations
Characteristics and conditions of data_usage of data rising in importance globally
Classification of risks_fringe risks
Current use of data_analysing clients to track trends and changing behaviours
Current use of data_analysing past activity patterns
Current use of data_analysing the data to predict performance trends
Current use of data_analysing the economy to predict performance trends
Current use of data_assessing how stable an industry is
Current use of data_assessing impact of Covid
Current use of data_cost management analytics
Current use of data_development of customer propositions
Current use of data_drive decisions at different levels through organisation
Current use of data_drive discipline in desired behaviours
Current use of data_for strategic decision making
Current use of data_forecasting longterm trends
Current use of data_forecasting product sales trends
Current use of data_identifying challenges and solutions related to Covid impact
Current use of data_identifying mega trends
Current use of data_managing operating expenses
Current use of data_navigating uncertainty in complex and ambigious environments
Current use of data_navigating uncertainty in forecasting
Current use of data_predict future events and outcomes
Current use of data_projecting revenue growth prospects
Current use of data_push performance targets
Current use of data_short term trends
Current use of data_staffing trends and wellness
Current use of data_to effect day to day operations
Current use of data_tracking financial performance
Current use of data_tracking trends in other markets
Data lessons from covid_access to data analysis scientist skills is essential
Data lessons from covid_best supported by establishing database structures
Data lessons from covid_critical value of having data to keep abreast with new trends
Data lessons from covid_data is only as useful as the quality of decisions it enables
Data lessons from covid_difficult to assess data sources

Data lessons from covid_importance of analysing data deeply
Data lessons from covid_importance of assessing and selecting data to guide decisioning
Data lessons from covid_importance of constant analysis of client data for new needs
Data lessons from covid_importance of constant analysis of historical data
Data lessons from covid_importance of data as a risk mitigating tool
Data lessons from covid_importance of having quick information available
Data lessons from covid_importance of investing in data management systems and capabilities
Data lessons from covid_importance of listening to data above the noise of subjective sentiment
Data lessons from covid_importance of using a variety of data sources to support decisioning
Data lessons from covid_importance of using data from credible sources
Data lessons from covid_insufficient current data makes it difficult to manage evolving situations
Data lessons from covid_insufficient current data makes it difficult to predict future scenarios
Data lessons from covid_self discipline required to seek and heed data based insights
Data lessons from covid_use of data for decisions is essential but not used effectively
Emerging approach to decisioning in uncertainty_establish data sourcing processes that ensure variability in sources used
Emerging approach to decisioning in uncertainty_follow set processes supported by right governance
Emerging approach to decisioning in uncertainty_recognising that data cannot be the sole criteria applied in formulating decisions
Emerging behaviours in data use for optimal decisioning_analyse value adding processes for opportunities to improve
Emerging behaviours in data use for optimal decisioning_annual ISO certification audits to uphold oversight of data integrity
Emerging behaviours in data use for optimal decisioning_asking divergent questions with potential influence on decision outcomes
Emerging behaviours in data use for optimal decisioning_building ability to represent and present data in various ways

Emerging behaviours in data use for optimal decisioning_development of a data management ecosystem combining internal and external capabilities
Emerging behaviours in data use for optimal decisioning_huge drive towards data driven decision making
Emerging behaviours in data use for optimal decisioning_increased investment in building BI capability
Emerging behaviours in data use for optimal decisioning_increased investment in digital technologies
Emerging behaviours in data use for optimal decisioning_ISO certification to ensure optimal data security standards are upheld
Emerging behaviours in data use for optimal decisioning_shift in decision power from consultants to clients
Emerging behaviours in data use for optimal decisioning_supported by client driven proof of concepts to test solutions
Emerging behaviours in data use for optimal decisioning_supportive executive behaviours in prioritising data use processes
Emerging behaviours in data use for optimal decisioning_track and measure behaviour of data tracking infrastructure to ensure integrity in data collected
Emerging behaviours in data optimisation for decisioning_encourage staff awareness and engagement
Emerging behaviours in data optimisation for decisioning_triangulate diverse data to set up assumptions
Emerging behaviours in data use for optimal decisioning_supported by outsourcing machine learning capabilities
Emerging sources of value inked to data usage_distinguish clients by behavior patterns
Emerging sources of value inked to data usage_empowering of individuals to make decisions
Emerging sources of value inked to data usage_giving individuals a distinctive edge to advance in profile
Emerging sources of value linked to data usage_business growth and expansion with investment into analytics technologies
Emerging sources of value linked to data usage_nurturing a culture of disciplined attention to accuracy
Emerging sources of value linked to data usage_raising consciousness of lower level staff impact on higher level staff

Emerging thinking in data optimisation for decisioning_align relevance of data to industry not professional discipline
Emerging thinking in data optimisation for decisioning_demystify the notion of what data is as relevant to set context
Emerging thinking in data optimisation for decisioning_firms lagging behind on realtime data capability are at risking their survival
Emerging thinking in data optimisation for decisioning_look for data that disproves assumptions
Established practice in managing risks_risk modelling
Impact of covid on business processes_communication processes taking longer delaying outcomes
Impact of covid on business processes_email engagement sidelined to fringe hours
Impact of covid on business processes_exposed weaknesses in current systems
Impact of covid on business processes_improved turnaround of decisions for smaller low risk projects
Impact of covid on business processes_more meetings being scheduled to facilitate alignment
Impact of covid on business processes_not anticipated to require additional usesr to access data software
Impact of covid on business processes_reduction in long meetings
Impact of covid on business processes_shift from collaborative discussion to data driven decision making
Impact of covid on business processes_travel restrictions have rendered some markets physically inaccessible
Impact of covid on business processes_unprecedented changes in changed consumer behaviour patterns
Impact of covid on business processes_use of data to predict how customers were set to be impacted
Impact of covid on business_client interaction centralised among more senior staff
Impact of covid on business_client interaction substituted with data analysis
Impact of covid on business_client led new product innovation
Impact of covid on business_constant communication through data and information sharing
Impact of covid on business_cost containment through sweating assets
Impact of covid on business_demand increases in medical supply industry

Impact of covid on business_demand increases in mining industry
Impact of covid on business_dramatic decline in activity levels
Impact of covid on business_expanded rate of learning
Impact of covid on business_future likely to be very different from the past
Impact of covid on business_growth in consulting firm activity
Impact of covid on business_heightened importance of data
Impact of covid on business_hiring additional staff to meet expanding demand for consulting services
Impact of covid on business_increased use of data to make critical decisions
Impact of covid on business_limited change to internal operating procedures
Impact of covid on business_loss of earnings for employees
Impact of covid on business_majority of staff working remotely from home
Impact of covid on business_negative economic effects projected to take years to recover
Impact of covid on business_rapid evolve of new ways of working
Impact of covid on business_rapidly changing business landscape
Impact of covid on business_rollout of cost containment strategies
Impact of covid on business_severely negative impact on the economy
Impact of covid on risk management approach_actively preparing for revenue threatening scenarios
Impact of covid on risk management approach_actively preparing for very unlikely scenarios
Impact of covid on risk management approach_cannot ignore sources of risk
Impact of covid on risk management approach_demands adaptability in all aspects of the firm
Impact of covid on risk management approach_development of backup plans to protect business sustainability
Impact of covid on risk management approach_heavily data driven decisioning environment
Impact of covid on risk management approach_raised active consciousness towards fringe risks
Impact of covid on risk management approach_review of contingency plans
Implications of uncertainty on management decisioning_slower turnaround of signoff on data driven decisions

Key skills and resources for data management processes_capability to analyse data to inform decisions

Key skills and resources for data management processes_capability to use database infrastructure

Key skills and resources for data management processes_database infrastructure

Key skills and resources for data management processes_Exco capability to run data management units

Key skills and resources for data management processes_individuals capable of extracting decisioning data requirements

Key skills and resources for data management processes_IT department

Key skills to manage uncertainty_ability to prepare for decision moments

Key skills to manage uncertainty_employ of hindisight experience in decisioning

Key skills to manage uncertainty_human diligence in overseeing accuracy in data analytics

Key skills to manage uncertainty_human intervention required to moderate subjective implications of data led decisions

Key skills to manage uncertainty_human understanding of inner workings of machine-led data analytics

Lack of distinction between risk and uncertainty.

Long established data driven culture

Management approach to decisioning in uncertainty_becoming comfortable with making data guided decisions

Management approach to decisioning in uncertainty_becoming comfortable with making decisions despite limited avaliable information

Management approach to decisioning in uncertainty_becoming comfortable with not knowing exact nature of outcomes

Management approach to decisioning in uncertainty_build clear justifications to support decisions

Management approach to decisioning in uncertainty_building multiple prediction scenarios for key decisions

Management approach to decisioning in uncertainty_disciplined in applying pre-set parameters when decision moments arise

Management approach to decisioning in uncertainty_drawing a disctinction between uncertain versus unprecedented conditions

Management approach to decisioning in uncertainty_embracing the challenge of making uncertain decisions

Management approach to decisioning in uncertainty_employ computers to reduce subjectivity in data analytics

Management approach to decisioning in uncertainty_employ data analytics machine learning to predict behaviours

Management approach to decisioning in uncertainty_employ of both quantitative and qualitative data to make decisions

Management approach to decisioning in uncertainty_employ the right tools to help frame decisions

Management approach to decisioning in uncertainty_entrenching and prioritising data usage behaviours

Management approach to decisioning in uncertainty_evaluate and weight decision parameters

Management approach to decisioning in uncertainty_get to know the market

Management approach to decisioning in uncertainty_having the courage to make a decision despite uncertainty

Management approach to decisioning in uncertainty_heavy reliance on data to guide long range strategic decisions

Management approach to decisioning in uncertainty_include a risk factor for error due to poor data quality

Management approach to decisioning in uncertainty_keep data processes simple

Management approach to decisioning in uncertainty_knowing when semi accurate data is sufficient

Management approach to decisioning in uncertainty_listening to customers and other affected stakeholders

Management approach to decisioning in uncertainty_making the most of what's available

Management approach to decisioning in uncertainty_managing any conflict between objective data outcomes and ethical implications

Management approach to decisioning in uncertainty_managing any conflict between objective data outcomes and other subjective influences

Management approach to decisioning in uncertainty_outsourcing projects

Management approach to decisioning in uncertainty_pay close attention to where data employed is sourced

Management approach to decisioning in uncertainty_prepare for potential crisis decisions well in advance to be unemotional
Management approach to decisioning in uncertainty_recognising that data is not the only criteria to consider fore decisions
Management approach to decisioning in uncertainty_set decision rules for repeated decisions extracted from credible data sources
Management approach to decisioning in uncertainty_set objective decision parameters premptively for key decisions
Management approach to decisioning in uncertainty_use data to predict future impact of Covid
Management approach to decisioning in uncertainty_use of data and data modelling
Management approach to decisioning in uncertainty_use of data from other more advanced markets
Management approach to decisioning in uncertainty_use of data to identify implications of uncertainty
Management approach to decisioning in uncertainty_use of data to make contentious decisions
Management approach to decisioning in uncertainty_use of data to make difficult decisions
Management approach to decisioning in uncertainty_watching competitor and stakeholder activity
Managers are evaluated through quality decisions not quality data
Managing uncertainty approach_avoidance of loss due to prediction error
New reality of a data driven world_requires proactively enagaged individuals
Opportunities for improved data usage_access to better quality data for quality decisions
Opportunities for improved data usage_employ machine intelligence to assess relevance
Rate of advancement in data manipulation competencies within firms_limited
Rate of advancement in data usage competencies within firms
Recognition of the high dependency of decision making on accurate data
Recommendations for improved decisioning during uncertainty_collaborative approach to building interpretations fro available data
Recommendations for improved decisioning during uncertainty_communicating data insights effectively
Recommendations for improved decisioning during uncertainty_companies must invest in integrated systems

Recommendations for improved decisioning during uncertainty_companies must invest in making data analysis interaction ubiquitious across the firm
Recommendations for improved decisioning during uncertainty_companies must invest in systems with realtime data tracking capability
Recommendations for improved decisioning during uncertainty_companies must recruit data analytics skilled staff across all departments in the firm
Recommendations for improved decisioning during uncertainty_developing positive mindsets towards open sharing of data
Recommendations for improved decisioning during uncertainty_employ inhouse data scientists to drive analytics capabilities
Recommendations for improved decisioning during uncertainty_invest in data scientists to drive analytics
Recommendations for improved decisioning during uncertainty_invest in database infrastructure
Recommendations for improved decisioning during uncertainty_sharing of information and data across communities of decision makers
Recommendations for improved decisioning with data_move away from an IT department led competency to an organisation wide data usage capability
Respondent's level in the organisation_senior management
Respondent's organisation profile_local and regional offices
Respondent's organisation size_large
Respondent's organisation size_medium
Respondent's organisation size_small
Respondent's role_client facing
Respondent's scope of work_Exco executive
Respondents' current roles
Respondents' current roles_regional portfolio oversight
Role of data in decision making_better quality improves short term risk management
Role of data in decision making_enable consistently objective decision making
Role of data in decision making_narrow parameters for required decisioning
Role of data in decision making_objective moderater of contentious outcome
Role of data in decision making_set parameters for required decisioning
Role of data in decision making_tool for stakeholder engagements & negotiations
Role of data in identifying & reinforcing sources of risk
Role of data mangement sytems_enable consistently objective solutions to be identified

Sources of data_customers
Sources of data_external sources
Sources of data_internal sources
Sources of data_retail channels
Sources of decisioning inefficiencies_ineffective purpose alignment across staffing levels
Sources of decisioning inefficiencies_lack of cohesive internal understanding
Sources of decisioning inefficiencies_lack of transparency
Sources of decisioning inefficiencies_poor communication of roles and their impact
Sources of decisioning inefficiencies_tension between economic modelling assumptions about accuracy of data versus reality
Sources of decisioning inefficiencies_tension between economic modelling assumptions about human nature versus reality
Sources of operational risk_ increased role of technology in decision making
Sources of operational risk_bias from human interface required for data management
Sources of operational risk_having a lot of data on the cloud
Sources of operational risk_staff working from home
Target outcomes of data usage in decisioning_financial gains
Target outcomes of data usage in decisioning_improved chance of making correct decisions
Types of data _customer behaviour patterns
Types of data _realtime data
Types of data _revenue activity
Types of data _sales commissions
Types of data_current data
Types of data_daily sales dashboards
Types of data_firm concrete data generated from activities
Types of data_GDP projections
Types of data_historical data
Types of data_operating expenses
Types of data_qualitative information from stakeholder relationships
Types of data_staff employment costs
Uncertainty management lessons from covid_ capability to access realtime data is essential to navigate uncertainty
Uncertainty management lessons from covid_ confronting the unknown character & duration of the pandemic

Uncertainty management lessons from covid_ confronting the unknown character of post uncertainty motivated decision outcomes

Uncertainty management lessons from covid_ confronting the unknown character pandemic with no data to help navigate decisions

Uncertainty management lessons from covid_ data is unable to guide decisioning in unprecedented conditions

Uncertainty management lessons from covid_ increased risk of making questionable decisions when data is limited and delayed

Uncertainty management lessons from covid_ intensified sensitivity to time lags in accessing data

Uncertainty management lessons from covid_ recognise that everyone is one is trying to figure out the changing reality

Uncertainty management lessons from covid_ time to do away with legacy systems that create departmental silos

Uncertainty management lessons from covid_ unprecedented situations are pregnant with unknowns

Uncertainty management lessons from covid_ unpredictable depth of decline in activity levels

Uncertainty management lessons from covid_ unpredictable rate, path and extent of post pandemic recovery

Uncertainty management lessons from covid_ we don't know how to navigate unprecedented situations in the moment

Uncertainty management lessons from covid_appreciation of improved decision quality from timely data

Uncertainty management lessons from covid_improved quality of decisions and outcomes enabled by data

Unique needs from data_to see big picture scenarios of future opportunities

Value of automated decision processes_access to set desired formats of data processing

Value of automated decision processes_facilitates quick identification and reaction to anomalies

Value of data driven decisioning_able to track data over long periods of time improving reliability of insights

Value of data driven decisioning_enables greater accuracy in decisions

Value of data driven decisioning_enhances objectivity in decisioning

Value of data driven decisioning_facilitates automation of repeatedly required decisions
Value of data driven decisioning_facilitates faster decision making for projects
Value of data driven decisioning_facilitates objective decision making
Value of data driven decisioning_facilitates rapid identification of decision options
Value of data driven decisioning_improved the process of identifying decision anomalies
Value of data driven decisioning_mediates

APPENDIX 4: ETHICAL CLEARANCE LETTER

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Munyaradzi James Hove,

Please be advised that your application for Ethical Clearance has been approved.
You are therefore allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

[Ethical Clearance Form]

Kind Regards

This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIBS Research Admin team.