Gordon Institute
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Leveraging big data analytics and capabilities for data-driven decision-making in South African banking

By

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ABSTRACT

Despite the widespread attention given to big data and analytics, there is still a lack of clarity regarding the success rate of big data initiatives and their strategic value. While existing literature primarily emphasizes the enhancement of tactical organizational capabilities through big data and analytics, there is a notable scarcity of studies that delve into their impact on organizational decision-making. Moreover, a limited conceptual framework explores how big data and analytics create strategic value for organizations through data-driven decision-making. This study aims to fill this gap by investigating how big data analytics and capabilities can be effectively applied for data-driven decision-making, specifically examining factors that either facilitate or hinder the South African banking sector's ability to harness these technologies for strategic decision-making. Through thematic analysis from the qualitative interview data, the findings underscore the critical need for aligning data and business strategies, effective data leadership, and fostering a data-driven culture to leverage big data analytics into data-driven decision-making within the South African banking sector.

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KEYWORDS

Big Data Analytics, Big Data Capabilities, Decision-making, Data-driven decision-making, Banking sector

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DECLARATION

I declare that this research project is my work. It is submitted in partial fulfillment of the requirements for the degree of Master of Philosophy in Corporate Strategy 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 authorization and consent to conduct this research.

Yvonne Sindiswa Moyikwa

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1 CHAPTER 1: INTRODUCTION TO THE RESEARCH PROBLEM

The research investigates how big data analytics can be leveraged into data-driven decision-making within the South African banking sector. The study aims to extract valuable insights for proposing strategic applications of big data analytics in the banking sector by utilizing qualitative interview data and conducting thematic analysis. The focus is on understanding the factors influencing the success of big data analytics and investigating the conditions under which big data analytics capabilities can improve decision-making.

The research study brings value to academia by examining empirical relationships in data-driven decision-making in the South African banking industry during the era of big data analytics. It is expected to contribute substantially to the literature of big data analytics, providing insights into its effective utilization in decision-making processes.

Additionally, the study contributes by revealing the connections between big data analytics capabilities and data-driven decision-making. The insights derived from these findings are valuable for business practitioners, offering guidance for informed decisions on the optimal use of big data analytics in shaping data-driven decision-making processes within the banking industry.

This chapter establishes the research context by presenting it from a business and academic perspective and outlining the research aim. Big data analytics is utilized in the banking industry; nevertheless, there is limited research on how big data analytics can be leveraged in data-driven decision-making.

1.1 Contextual Background

Organizations neglecting the strategic significance of big data will lose their competitive advantage (Elia et al., 2022; Grover et al., 2018). In the current highly competitive business environment, businesses are required to adapt quickly to shifting market demands; big data analytics is critical in curating and converting the raw big data into valuable information and knowledge for businesses to adapt to change and remain competitive in the fiercely contested markets (Dong & Yang, 2020; Grover et al., 2018) as is evident from IBM Institute for Business Value, MIT Sloan Management Review, and 2018 McKinsey & Company Report research revealing that highly successful companies employ analytics five times more frequently than their less successful counterparts, underscoring the substantial impact of big data analytics on their achievements (LaValle et al., n.d.). Elia et al. (2022) concurs with this study, asserting that big data has surfaced as a driver for innovation and a source of competitive advantage, transforming decision-making processes and potentially opening avenues for novel strategic approaches.

Moreover, the significant growth of data from various sources and in multiple forms has led to a growing focus on big data and business analytics (Boldosova & Luoto, 2019). Big data continuously produces overwhelming data that exceeds what organizations can effectively utilize (Boldosova & Luoto, 2019; Mikalef et al., 2019a). It is distinguished by its remarkable scale, rapid velocity, and diverse variety (Diebold, n.d.; Fosso Wamba et al., 2015; Mikalef et al., 2020). Volume refers to the vast quantity of data generated daily, velocity indicates the rapid rate at which information can be accessed, and variety encompasses the wide range of sources from which the data originates (Elia et al., 2020; Mikalef et al., 2020).

Within the South African banking sector, Pillay and Van der Merwe (2021) contend that despite having access to a substantial volume of big data from various transactions, only a limited number of organizations capitalize on this wealth of detailed, raw data to extract valuable insights into consumer behavior for predictive analytics (Hung et al., 2020). This data, sourced from customer transactions, loan applications, and credit card activities, is valuable for commercial banks (Hung et al., 2020; Pillay & Van der Merwe, 2021; Soldatos & Kyriazis, 2022). Brocchi et al. (2018) noted that leading financial institutions that previously utilized descriptive analytics to guide decision-making are currently incorporating analytics into products, processes, services, and numerous front-line operations. The utilization of big data analytics has proven effective in augmenting these efforts for the banks (Hung et al., 2020).

Despite substantial investments in data assets to maintain competitiveness and comply with regulatory requirements, South African banks, as noted by Pillay and Van der Merwe (2021), face difficulties in efficiently leveraging data analytics to extract significant value from their data initiatives (Brocchi et al., 2018). Hung et al. (2020) assert that incumbent banks possess a competitive advantage through their substantial historical customer data. However, uncertainty lingers about the ability of banks to translate this data into tangible advantages (Brocchi et al., 2018; Hung et al., 2020).

Both the business world and academia are deeply engaged in exploring the potential opportunities that big data can offer to organizations (Awan et al., 2021; Brocchi et al., 2018; Mikalef et al., 2019b; Wamba et al., 2017). Most research focuses on the various analytical methods being utilized to effectively derive insights from big data (Awan et al., 2021), while other studies focus on how companies leverage big data to discover concealed insights, enhance decision-making, and facilitate strategic decision-making (Awan et al., 2021; Mikalef et al., 2020) and others have focused extensively on the significance of particular big data skills and capabilities for achieving organizational success (Akhtar et al., 2019). Mikalef et al. (2019b) suggest that "current empirical research on the value of big data analytics is in its early stages, a surprising situation considering the increasing number of companies investing in big data. Existing reports on the business value of big data primarily come from consultancy firms, the popular press, and individual case studies, lacking substantial theoretical insights. Consequently, there is a limited understanding of how companies should navigate their big data initiatives, and there is insufficient empirical evidence to substantiate the assertion that these investments yield measurable business value."

The existing literature has left a noticeable void in exploring the correlation between the competencies of cross-functional teams, their interconnections, their influence on pertinent data-driven initiatives, and the broader impact on business performance (Akhtar et al., 2019). Notably, while some research has indicated that businesses leveraging big data analytics for decision-making tend to excel in areas such as risk management, operational efficiency, and customer experience (Awan et al., 2021; Yasmin et al., 2020), other scholars exemplified by Mikalef et al. (2019a) and Grover et al. (2018), have delved into the correlation between business analytics, business performance, the potential for transformative value creation through big data analytics, and its pivotal role in strategic planning.

However, Grover et al. (2018) further argue, "Despite the publicity regarding big data and analytics, the success rate of these projects and strategic value created from them are unclear. Most literature on big data and analytics focuses on how it can enhance tactical organizational capabilities, but very few studies examine its impact on organizational value. Further, there is limited framing of how big data and analytics can create strategic value for the organization. After all, the ultimate success of any big data and analytics project lies in realizing strategic business value, which gives firms a competitive advantage". This aligns with the argument put forth by Awan et al. (2021) and Rialti et al. (2019), arguing that despite the potential of big data analytics, there is a notable scarcity of empirical research investigating the factors that contribute to data-driven insights that impact on enhancing the quality of decision-making, particularly in the context of strategic decision-making. Ghasemaghaei et al. (2018) further state that despite its importance, there remains a lack of comprehension of how competency in data analytics influences decision-making within a firm, while Mikalef et al. (2020) argue that despite limited evidence indicating the value generation potential of big data analytics, the assertion that investments in big data analytics leading to competitive advantages warrant a more thorough examination.

While the critical role of big data analytics in organizations, particularly within the banking sector, has been acknowledged and investigated to some extent (Awan et al., 2021; Grover et al., 2018; Rialti et al., 2019), there exists a substantial gap in understanding the specific impact of big data analytics capabilities on strategic decision-making. Despite the increasing body of research and technological advancements in the broader field of big data analytics (Grover et al., 2018), a persistent knowledge gap persists, hindering a comprehensive understanding of how these capabilities influence decision-making processes in organizations (Awan et al., 2021; Grover et al., 2018; Rialti et al., 2019).

Moreover, the literature reveals a critical need to explore how insights generated through big data analytics capabilities can reshape a company's strategic trajectory, positioning it ahead of competitors (Mikalef et al., 2021). Although the banking industry leads in the adoption of big data analytics, unlike sectors such as pharmaceuticals, insurance, energy, manufacturing, and agriculture (Hung et al., 2020; Pillay & Van der Merwe, 2021), it faces persistent challenges in fully integrating these analytics into its organizational culture, decision-making procedures, and day-to-day operations (Brocchi et al., 2018). This discrepancy between adoption and integration within the banking sector highlights an unexplored research area concerning the barriers and facilitators in aligning big data analytics with strategic decision-making processes.

Furthermore, despite the substantial investment made by the banking sector in data analytics, particularly attributed to its association with heightened productivity (Elia et al., 2022; Gul et al., 2023), there is a lack of nuanced understanding regarding how these investments translate into effective strategic decision-making. Therefore, research is urgently needed to explore the intricate dynamics between big data analytics investments, organizational practices, and strategic decision outcomes in the banking sector, providing valuable insights for academia and industry practitioners.

Nevertheless, Mikalef et al. (2021) find this surprising, given that one of the fundamental premises of employing big data analytics in organizational contexts is the expectation that these technologies can yield transformative insights, shaping the strategic trajectory of firms ahead of their competitors by making data-driven decisions. Therefore, this study focuses on the factors that facilitate or impede the South African banking sector's ability to effectively utilize big data analytics and leverage these technologies to their fullest potential by driving a data-driven culture that will lead to decision-making.

1.1.1 The South African Banking Institutions

The banking industry in South Africa comprises 67 banks with different ownership structures. Among these, nineteen percent are under local control; foreign entities control nine percent, forty-three percent operate as representatives of foreign banks, nineteen percent function as branches of foreign banks, and four percent are mutual banks. The remaining four percent are banks currently in the process of liquidation (South African Reserve Bank, 2020). The South African banking sector is characterized by stringent regulations enforced by the South African Reserve Bank, indicating its well-developed nature. This resilience was evident during the global financial crisis in 2008, as the South African financial sector experienced comparatively milder repercussions than certain other countries worldwide. These regulations impose the responsibility on banks to handle their data effectively, ensuring consistency in risk management, combating financial crimes, and safeguarding customers from financial difficulties and irresponsible lending practices (National Treasury South Africa, 2021). As stated in the banking supervision report published by the South African Reserve Bank (2017), the leading four central banks in South Africa are Standard Bank of South Africa Limited, FirstRand Bank Limited, Absa Bank Limited, and Nedbank Limited. These banks continue to maintain their positions as the top four banks in South Africa based on their assets, as affirmed by PwC (2020). This study will, therefore, focus on the four major banks.

1.1.2 Big Data Analytics

The term big data was made famous around 1998 by John R Masey, a computer expert working as a chief scientist at Silicon Graphics Inc. (Diebold, 2012; Gu et al., 2017). Gu et al. (2017) further state that John R Masey used "big data" to describe the substantial volume of generated data. This data is also distinguished by its velocity and diversity because it can be structured or unstructured and includes things like photographs, audio, videos, and graphics (Gu et al., 2017). Big data analytics gained prominence in 2003 as companies like Google, Yahoo, and other high-tech firms began leveraging large-scale data for business analysis and derived valuable insights from the data (Gu et al., 2017). Despite the increasing number of companies entering the field of big data analytics, empirical research on its competitive potential is still in its early stages (Mikalef et al., 2020). Nevertheless, Mikalef et al. (2021) find this unexpected, considering that one of the fundamental principles of utilizing big data analytics in organizational contexts is the anticipation that these technologies can produce transformative insights, guiding firms' strategic direction ahead of their competitors.

While big data analytics has been widely recognized as a significant technological advancement in both academic and business circles, there is a need for effective and efficient analysis, interpretation, and prediction to explore the rewards that lie ahead by using datasets that are enormous, highly complicated, and unmanageable by conventional applications (Mikalef et al., 2020). The data analysts or scientists use mathematical models to mine this big data and find knowledge, insights, and foresight from the hidden patterns (Mikalef et al., 2020).

1.1.3 Strategic Decision-making

Strategy is the action plan designed to use and deploy business resources toward achieving competitive advantage and sustainability (Lynch and Mors, 2019). The strategy is critical to businesses' performance and survival because it influences the management and usage of business internal resources, response to ever-changing external environments, and the competencies of generating value (Ghasemaghaei, 2019; Grover et al., 2018). In navigating the ever-changing business landscape, organizations must craft effective strategies to attain their objectives and ensure sustainability (Lynch and Mors, 2019). According to Brocchi et al. (2018), financial institutions, in particular, require a well-defined data strategy to leverage the vast potential of big data analytics.

Awan et al. (2021) state, "Given the importance of big data analytics in organizations, its role in strategic decision-making is becoming an important field of inquiry." Grover et al. (2018) further argue that despite the increasing interest in big data research in recent years, there remains a scarcity of studies specifically centered on the strategic business value of big data that impacts data-driven decision-making. According to Ghasemaghaei (2019), decision-making refers to a company's ability to make precise and accurate decisions and is acknowledged as a vital capability.

1.2 The relevance of the research from a business perspective

Big data analytics are a valuable resource that may help businesses perform better and gain a competitive edge (Elia et al., 2022). Many businesses have adopted big data analytics, and this has come with a significant investment in infrastructure, technology, specialized skill, and knowledge in managing and interpreting the data to better the business (Chen et al., 2022); this is aligned with a recent survey from the Harvard Business Review (Nair, S., 2020) and 2018 McKinsey & Company Report (Brocchi et al., 2018) which found that businesses globally spend almost $40 billion annually on data analytics technology and services. However, many large corporations have not yet developed a data culture, and about half are not effectively competing on data and analytics. A data-driven organization requires technology, data, internal processes, and culture to incentivize data-driven decisions (Nair, 2020). Côrte-Real et al. (2019) argue that big data analytics is often recognized as a crucial factor distinguishing high-performing organizations from low-performing ones. Additionally, Yasmin et al. (2020) supports the idea that companies employing data-driven approaches in decision-making are more profitable and productive compared to their competitors

The usage of big data analytics has significantly increased because of the exponential growth of data and consequent technical developments. According to Mikalef et al. (2020), up until this point, the media, consultancy companies, and individual case studies that lack theoretical understanding have reported on the business usefulness of big data. Businesses must employ big data analytics to handle this information's unparalleled volume, velocity, diversity, authenticity, and value to manage and utilize big data from their platforms for decision-making (Lehrer et al., 2018). Additionally, there must be an embracement of new viewpoints comprehending client behavior and developing innovative marketing strategies that are data-driven (Mikalef et al., 2020). Numerous empirical studies have suggested that a significant number of businesses struggle to extract value from their investments in big data analytics; this challenge often stems from managers' reluctance to adopt new technologies or the reluctance of various departments to collaborate and share data results in the creation of silos that impede the efficient utilization of big data (Mikalef et al., 2021).

Scholars like Awan et al. (2021) and Rialti et al. (2019) have pointed out the lack of sufficient research on how the use of big data analytics has influenced organizations in making data-driven decisions that shape their future direction, optimize internal resources, and create novel value propositions. According to Pillay and Van der Merwe (2021), the South African banking sector has substantially invested in data assets to stay competitive and comply with regulatory demands. However, these banks are encountering difficulties in effectively utilizing data analytics to achieve a competitive advantage and improve their profitability; this is aligned with a recent study by Khanna and Martins (2018) stating that "most major banks have the tools and advantages to push the boundaries of their existing business models. Moreover, they are certainly motivated. What hampers their progress is uncertainty about how best to build on core and should invest in—new digital capabilities in areas like design, innovation, data and analytics, personalization, and digital marketing".

This research will focus on filling the more qualitative exploratory research gap within big data analytics capabilities and data-driven decision-making within the South African banking sector. The qualitative analysis offers detailed insights into the crucial factors that must be included in a model for future quantitative testing. This research seeks to identify the key variables contributing to big data analytics and data-driven decision-making, promoting convergence in the literature. Taking this approach will allow the findings obtained from the analysis to support the formulation of conclusive outcomes regarding the crucial elements of big data analytics capabilities and their influence on data-driven decision-making.

1.3 The grounding of the research from a theoretical perspective

Analytics has become a top priority for the C-suite (Dong & Yang, 2020; Grover et al., 2018). Since management operates in extraordinarily complex and highly regulated business environments, decision-makers can not solely rely on their intuition (Ghasemaghaei, 2019). As a result, businesses must depend more and more on their analytical abilities to enhance their decision-making skills (Dong & Yang, 2020). However, according to Awan et al. (2021), limited emphasis has been placed on understanding the impact of big data analytics on decision-making within organizations. Although it is gaining more popularity, the academic literature on data analytics capability is still not well-developed, as published by Dubey et al. (2021), Mikalef et al. (2019a), and Mikalef et al. (2021).

Big data analytics can turn enormous amounts of raw, unstructured, and structured data into useful insights that are critical and valuable to business decisions (Dong & Yang, 2020). Mikalef et al.(2019b) characterize big data analytics as a potential catalyst for dynamic capabilities and enhanced decision-making. Given the perpetual challenge for organizations to establish a competitive advantage, there remains a need for a clearer understanding regarding the success rate and strategic value generated by big data analytics in contributing to strategic decision-making (Awan et al., 2021; Ghasemaghaei et al., 2018; Grover et al., 2018; Rialti et al., 2019).

According to Khanna & Martins (n.d.) and Soldatos & Kyriazis (2022), it is emphasized that despite the banking sector having access to significant amounts of structured, semi-structured, and unstructured data through monitored financial transactions, this valuable reservoir of big data is frequently underutilized. The effective harnessing of the potential of big data faces two primary challenges, as outlined: firstly, the sheer volume of data surpassing the capacities of traditional methods, and secondly, the reluctance of data scientists to adopt methodological changes due to skepticism about their perceived value. Awan et al. (2021), Grover et al. (2018), and Rialti et al. (2019) further confirm that despite the increasing amount of research on big data analytics and advancements in information technology capabilities, there remains a considerable knowledge gap regarding the impact of big data analytics capabilities on strategic decision-making.

While a growing body of empirical support indicates a positive correlation between well-informed decision-making and firm performance in developed countries (Gul et al., 2023), there is a notable absence of large-scale studies in the context of emerging economies (Chiheb et al., 2019). Despite the growing acknowledgment that data-driven decision-making holds significant promise for the financial sector, there is a scarcity of empirical evidence on the impact of such decision-making on financial performance within this industry (Gul et al., 2023). Addressing these notable gaps is pivotal in the current body of knowledge, as there is a restricted understanding of how big data analytics can be effectively used within organizations and the precise mechanisms through which value can be generated (Mikalef et al., 2019b).

1.4 The research questions.

This study aims to delve into the multifaceted role of big data analytics in shaping the effectiveness of data-driven decision-making. By addressing how big data analytics contributes to decision-making processes, the research seeks to unravel the impact of leveraging analytical tools on decision-making and efficiency. Additionally, the study aims to scrutinize the influence of organizational culture and leadership on the successful implementation of big data analytics. The research aims to uncover key factors that can either facilitate or hinder the adoption of big data analytics by exploring the intricate relationship between leadership, organizational culture, and the integration of big data analytics. Furthermore, the study provides insights into strategies for seamlessly integrating big data analytics into existing organizational structures and data-driven decision-making processes. By addressing these questions, the research aims to contribute valuable recommendations to enhance the strategic decision-making capabilities of organizations within the South African banking sector.

For this purpose, this study poses the following three research inquiries:

- How does big data analytics contribute to the effectiveness of data-driven decision-making?
- How does your organizational culture and leadership impact the successful implementation of big data analytics for data-driven decision-making?
- How can big data analytics be effectively integrated into organizational structures and decision-making processes to enhance strategic decision-making?

1.5 The research aims

As discussed above, academics and business experts disagree over how to accomplish the impact of big data analytics on data-driven decision-making and whether there is a link between an organization's ability to use data effectively and its decision-making ability. Invitations from researchers like Awan et al. (2021), Chen et al. (2022), Grover et al. (2018), Li et al. (2022), and Mikalef et al. (2021) suggest that there should be future studies that will examine the impact of the big data analytics on strategic decision-making, as previous research has shown that in addition to integrating big data analytics capabilities, other types of capabilities, such as tangible and intangible resources, may also be integrated.

Therefore, this research aims to delve into the multifaceted role of big data analytics in shaping the effectiveness of data-driven decision-making. Additionally, the study aims to scrutinize the influence of organizational culture and leadership on the successful implementation of big data analytics. The research aims to uncover key factors that can either facilitate or hinder the adoption of these technologies by exploring the intricate relationship between leadership, organizational culture, and the integration of big data analytics. Moreover, the study aims to offer valuable insights into strategies for seamlessly integrating big data analytics into the current organizational structures and decision-making processes. By addressing these questions, the research seeks to contribute practical recommendations to enhance the strategic decision-making capabilities of organizations within the South African banking sector.

This research will assist the South African banking industry in gaining insights on how to develop big data analytics capabilities that can be leveraged into data-driven decision-making as it responds to the organizations' request for assistance in utilizing big data effectively and extracting value that can lead to decision-making from big data analytics (Awan et al., 2021; Grover et al., 2018; Mikalef et al., 2020).

The aim will, therefore, be:

- To critically assess the big data analytics strategies of major retail banks in South Africa.
- To investigate the challenges that hinder these major banks from effectively utilizing big data to enhance data-driven decision-making that aligns with business objectives.
- To develop recommendations to enhance the effectiveness of big data analytics, focusing on driving decision-making that positively impacts the overall business strategy.

1.6 The research contribution

The research study adds value to academia by elucidating empirical relationships related to data-driven decision-making within the South African banking industry amid the era of big data analytics. Consequently, this study is poised to significantly contribute to the literature on big data analytics, shedding light on its effective utilization and integration into the decision-making process.

Moreover, the research study contributes by uncovering the connections between big data analytics capabilities and data-driven decision-making. The insights from these findings offer valuable guidance to business practitioners, enabling them to make well-informed decisions regarding the optimal use of big data analytics in shaping data-driven decision-making processes.

1.7 The research scope

This research focuses on how big data analytics and capabilities can be leveraged into data-driven decision-making within the South African banking sector. Through thematic analysis of the qualitative interview data, the study will gain valuable insights that will be used as recommendations for the strategic use of big data analytics on data-driven decision-making within the South African banking industry. This endeavor will be instrumental in comprehending the factors contributing to the success of big data and exploring the contexts in which big data analytics capabilities can augment decision-making. The study will evaluate critical aspects such as management, technology, talent, and strategic capabilities that are indispensable for effective decision-making, all while identifying significant challenges.

1.8 Conclusion

This chapter commenced by presenting a contextual background to the research problem and exploring the research's significance from both a business and theoretical standpoint. It introduced the research questions and aimed to guide the subsequent chapters.

Chapter 2 offers a comprehensive literature review, setting the foundation for the study, while Chapter 3 details the research questions. The research design and methodology are expounded upon in Chapter 4, and Chapter 5 presents the obtained results. A thorough discussion of these results is undertaken in Chapter 6, leading to the study's conclusion in Chapter 7.

2 CHAPTER 2: LITERATURE REVIEW

This chapter delves into big data analytics and examines the landscape of data-driven decision-making as portrayed in the academic literature. It aims to grasp the existing knowledge and pinpoint the gaps. Additionally, it seeks to articulate the challenges inherent in research, particularly in utilizing big data analytics for data-driven decision-making. Furthermore, it aims to comprehend better the recent literature on big data analytics, its capabilities, and data-driven decision-making.

The table below illustrates the logic and flow of the chapter.

Table 1: Literature Review Layout

Literature Review Layout
Introduction: Section 2.1 This section summarises the recent literature on big data analytics in organizations and developing capabilities, particularly in banking, to effectively leverage big data analytics for informed decision-making.
Big data analytics and capabilities: Section 2.2 This section details the recent literature on big data analytics in organizations, and introduces big data analytics capabilities
Big data resource requirement: Section 2.2.1 Drawing from the Research-Based view, this section highlights the capabilities needed for leveraging big data analytics in decision-making
Big data analytics in banking: Section 2.3 This section highlights the importance of big data analytics in the banking industry.
Decision-making: Section 2.4 This section details the recent literature on decision-making within organizations and introduces the variables that add nuance and context to the study
Data-driven decision-making: Section 2.4.1 This section explains the importance of data-driven decision-making
Big data analytics and decision-making: Section 2.4.2 Drawing from the recent literature, this section underscores the importance of big data analytics in decision-making
Leadership: Section 2.4.3 This conveys the leadership's crucial role in fostering capabilities necessary for effective decision-making using big data analytics.
Literature Review Conclusion: Section 2.5 This section concludes with recent literature on big data analytics and its effectiveness in data-driven decision-making. It proposes a conceptual research framework for the study.
Research Model Framework: Section 2.5.1

2.1 Introduction

The recent literature that examines how big data analytics can aid in making well-informed decisions has primarily concentrated on the impact it has on the performance of organizations (Dubey et al., 2021; Elia et al., 2020; Ghasemaghaei et al., 2018; Mikalef et al., 2020). The process of big data analytics entails the analysis and interpretation of data to generate actionable insights, offering a potential competitive advantage (Bahrami & Shokouhyar, 2022; Mikalef et al., 2020) by making informed data-driven decisions (Chen et al., 2022; Mikalef et al., 2021) which can significantly influence a firm's performance, particularly in strategic decision-making (Awan et al., 2021; Elia et al., 2022). However, Akhtar et al. (2019) argue that for big data analytics to be effective and better understood to contribute to a firm's better performance, big data analytics capabilities should be introduced as these play an essential role in managing ambiguous and challenging situations that influence decision-making. Big data analytics capabilities encompass a fusion of expertise, skills, and abilities in technology and management, enabling the exploration of data potential through advanced statistical, computational, and visualization tools (Chen et al., 2022). This is confirmed by Lehrer et al. (2018), stating that without big data analytics capabilities, organizations will not effectively extract knowledge from data and use it to make informed decisions, thereby supporting the creation of data-driven decision-making (Chen et al., 2022; Elia et al., 2022).

Within the banking industry, the substantial potential of big data analytics lies predominantly in enhancing customer loyalty and refining marketing strategies, as acknowledged by numerous enterprises and emphasized by Hung et al. (2020). As per the findings of Pillay and Van der Merwe (2021), banks possess the opportunity to improve their customer data, product offerings, risk assessment, and market projections; nevertheless, the conversion of analytical insights into concrete business outcomes has presented a significant challenge despite the adoption of analytics by these financial institutions (Hung et al., 2020; Pillay and Van der Merwe, 2021).

2.2 Big Data Analytics and Capabilities

The definition of big data analytics commonly centers on an array of technologies and architectures uniquely crafted to derive value from large and varied datasets (Dong & Yang, 2020; Elia et al., 2022). These technologies enable the rapid capture, discovery, and analysis of data at high velocities, making them a significant factor in determining firm performance (Elia et al., 2022; Mikalef et al., 2018). However, Chen et al. (2022), referring to Gupta and George (2016), argue that many claims regarding the benefits of big data analytics are based on anecdotal evidence provided by consultants. Nevertheless, a limited number of empirical research studies in this field have demonstrated a positive correlation between investing in the widespread implementation of big data analytics and improved performance (Ghasemaghaei, 2019). As a result, the primary advantage of big data analytics is its ability to facilitate more informed decision-making, which is less biased and grounded in empirical evidence (Awan et al., 2021; Yasmin et al., 2020).

Empirical studies from different scholars have consistently shown a positive relationship between the widespread use of big data analytics and enhanced performance (Akhtar et al., 2019; Awan et al., 2021; Mikalef et al., 2019a). The advantage lies in its ability to provide valuable insights for decision-making processes, leading to better-informed and evidence-based choices. Li et al. (2022) attest to this by stating that data analytics can enhance the efficiency and effectiveness of a company's decision-making by encompassing tasks such as capturing, storing, transmitting, sharing, searching, analyzing, and visualizing data.

Elia et al. (2022) and Mikalef et al. (2019a) define big data analytics as an advanced analytical method for managing large amounts of data that businesses use to understand their target markets and customers better, thereby exploring opportunities for competitiveness in today's thriving markets. Big data analytics is a crucial source of value that can provide a competitive advantage and improve business outcomes by making better decisions (Elia et al., 2022; Yasmin et al., 2020).

Previous studies have investigated how the quality of data and user experience with data usage impact a company's intention to acquire big data analytics solutions (Chen et al., 2022). Implementing big data analytics has become crucial in addressing distinct customer needs that are essential in establishing and preserving a competitive edge (Grover et al., 2018) by enhancing business performance (Elia et al., 2022) and improving decision-making processes (Sena et al., 2019; Yasmin et al., 2020). New opportunities for innovation in services are arising because of the growth in digital trace data and advancements in big data analytics by offering effective techniques and resources for collecting, handling, and examining substantial quantities of tracking information, allowing corporations to generate valuable perceptions by consolidating their clients' into a complete representation of their daily activities (Lehrer et al., 2018).

The rise of vast amounts of data, generated in real-time or near real-time and sourced from various platforms such as social media, online marketplaces, search engines, sensors, intelligent software, and the Internet of Things, has created a heightened demand for business analytics within organizations (Jha et al., 2020). By employing advanced analytical techniques in big data analytics, organizations have the potential to uncover valuable insights that greatly support complex decision-making processes (Lehrer et al., 2018; Müller et al., 2018). However, uncertainty in data introduces challenges that can amplify errors or flaws in the overall decision-making process (Ghasemaghaei et al., 2018). Given the significant impact of uncertainty on the accuracy of outputs generated by automated techniques, it becomes crucial to prioritize the reduction of uncertainty in big data analytics (Ghasemaghaei et al., 2018).

The implementation of big data analytics solutions, despite their significant financial investments, has become a vital undertaking for companies (Ghasemaghaei, 2019; Müller et al., 2018). These technologies enable companies to collect and analyze vast amounts of data from diverse business processes, providing a foundation for informed and strategic decision-making (Mikalef et al., 2021). However, it is essential to recognize that simply acquiring data through these technologies is insufficient for effective decision-making (Chen et al., 2022). The value of big data analytics lies in its capacity to drive service innovation and identify the critical factors necessary for developing new value propositions (Lehrer et al., 2018). Consequently, integrating and utilizing big data resources effectively, also known as big data analytics capability, has emerged as a crucial determinant of a company's performance, particularly its responsiveness to market demands (Chen et al., 2022). The growing importance of big data analytics capability underscores its indispensable role in decision-making (Bahrami & Shokouhyar, 2022). In simpler terms, big data analytics capability equips firms with the necessary skills and resources to handle large-scale data and generate insights that drive decision-making (Lehrer et al., 2018).

To create valuable knowledge and insights that guide decision-making, organizations need top-notch data, suitable information systems, analytical tools, and proficient human analytics talent (Chen et al., 2022; Dubey et al., 2021). However, the success of big data analytics relies on comprehending the factors that impact its effectiveness on a company's performance (Akhtar et al., 2019), leading to the introduction of big data analytics capability, which encompasses a combination of essential human resources, expertise in big data, advanced technologies, extensive datasets, and analytical methods (Elia et al., 2022; Mikalef et al., 2019b; Yasmin et al., 2020). The term "big data analytics capability" (BDAC), as described by Mikalef et al. (2020), refers to a company's proficiency in efficiently utilizing technology and expertise to gather, preserve, and analyze data to derive valuable insights. This capability enables companies to leverage the strategic significance of big data, which is still underutilized in the business world.

Recent research has established direct correlations between big data analytics capabilities and various aspects such as organizational performance, competitive advantage, decision-making effectiveness, business strategy coherence, and strategic business value (Bahrami & Shokouhyar, 2022; Grover et al., 2018; Elia et al., 2022; Chen et al., 2022). However, these studies primarily focus on the direct impact of big data analytics capabilities on organizational performance and do not investigate the mediating factors that could potentially influence this relationship (Elia et al., 2022; Mikalef et al., 2019b).

Leveraging big data analytics capabilities enables organizations to cultivate proficiency in extracting knowledge from data and comprehending the influence of data processing and analysis on decision-making, primarily through data visualization (Elia et al., 2022). Mikalef et al. (2019a) emphasize the importance of implementing specific procedures for utilizing big data, supported by Li et al. (2022), who emphasize the need for investment in necessary resources and their alignment with the company's strategy.

Furthermore, Mikalef et al. (2019a) investigate the relationship between a company's big data analytics capabilities and innovation capabilities, which are considered significant intangible resources. Drawing from the Resource-Based View (RBV) and the Dynamic Capability View (DCV), they suggest that a company's effective utilization of its big data analytics capabilities may depend on various factors, such as decision-making structure, organizational learning, and organizational culture (Ghasemaghaei et al., 2018), enabling the integration and analysis of diverse data sources into a unique and distinctive combination of conceptual elements specific to the organization over a significant period. As a result, big data analytics capabilities are categorized as inimitable resources (difficult for external actors to copy), rare (challenging to find or assemble in the market), non-substitutable (difficult to replace with other resources), valuable (generating economic value), and exploitable (creating an advantage that competitors cannot replicate) (Chen et al., 2022; Elia et al., 2022) which are the core components of the Resource-Based Theory.

The methods employed by big data analytics capabilities manage and refresh the company's set of resources and competencies, allowing it to integrate, construct, and adapt capabilities to address swiftly evolving environments. These approaches for generating value through big data analytics capabilities signify various avenues through which these capabilities can yield results that translate into actions impacting value

(Yasmin et al., 2020). According to Elia et al. (2022), there are four fundamental value-creation mechanisms: transparency, access, discovery, and proactive adaptation. Transparency involves open information and communication flows, while access refers to the availability and ability to use data. Discovery involves data-driven decision-making, and bold adaptation is the ability to keep up with market changes and requirements (Elia et al., 2022).

To utilize big data effectively for strategic decision-making, a firm needs a range of supportive resources that work together to enhance its overall big data analytics capabilities (Yasmin et al., 2020). Organizations need to obtain and cultivate a mix of technological, human, financial, and intangible assets to establish a challenging big data analytics capability to duplicate or transfer.

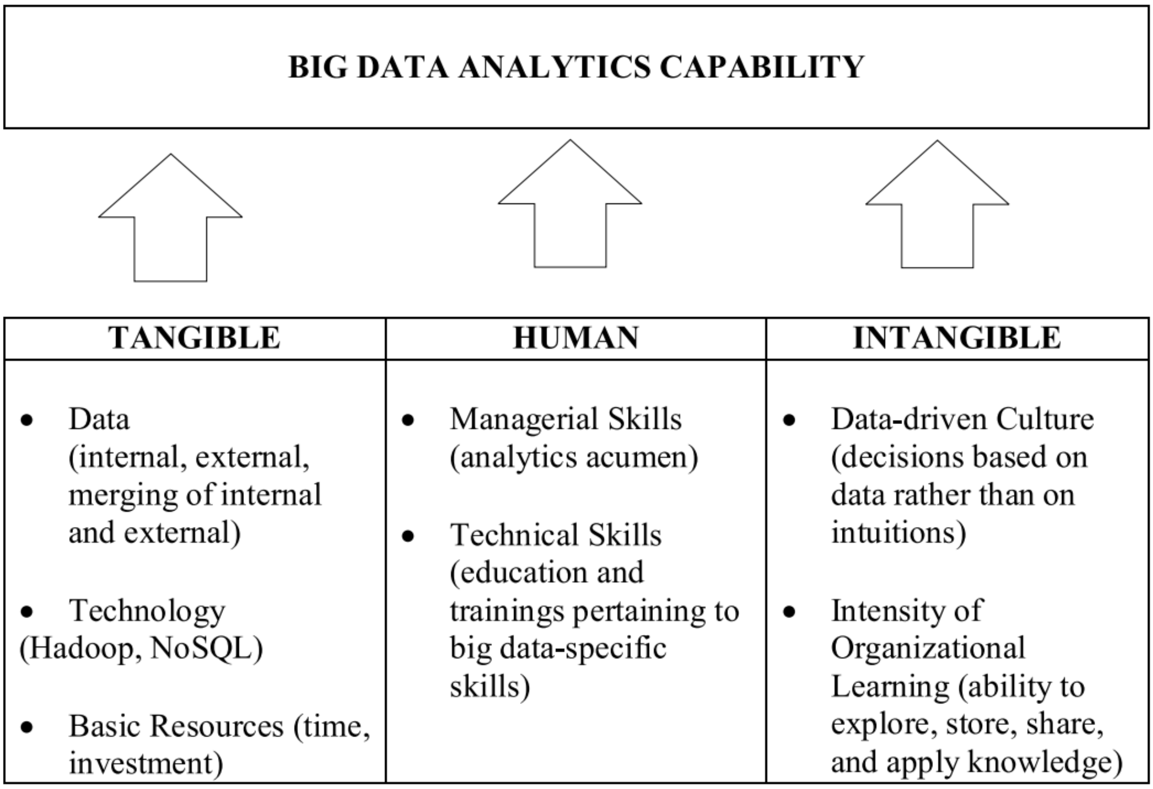
Organizations placing a premium on cultivating robust big data analytics capabilities can leverage it to shape strategies and guide decision-making processes at the highest management level. By investing in big data analytics capabilities, firms can accelerate their ability to generate insights, navigate intricate and rapidly changing environments, monitor their customers and competitors in real time, pinpoint operational inefficiencies and bottlenecks, and discern changes in the economic and business environment (Awan et al., 2021; Bahrami & Shokouhyar, 2022; Chen et al., 2022; Yasmin et al., 2020).

2.2.1 Big Data Resource Requirement

Drawing from the Resource-Based Theory, this influential framework below (Figure 1) provides valuable insights into how companies secure and maintain their competitive advantage by effectively managing their strategic resources (Mikalef et al., 2019a, 2019b). In alignment with the Resource-Based View, Mikalef et al. (2019b) conceptualize big data analytics capabilities as a firm's competence to collect and analyze data, generating insights by effectively utilizing data, technology, and talent across organizational processes, roles, and structures. This perspective broadens the understanding of big data by encompassing all relevant organizational resources crucial for transforming data into actionable insights applicable to operational and strategic decision-making (Mikalef et al., 2019b). Moreover, the importance of intangible resources, specifically a data-driven culture and organizational learning, is highlighted to implement big data initiatives successfully. A data-driven culture is emphasized as a key determinant of success in firms undertaking big data projects and continuous learning is deemed essential due to the dynamic nature of technologies associated with big data

(Mikalef et al., 2020).

Figure 1: *Big data analytics capabilities*



Source: *Adapted from* (Gupta and George, 2016, p. 1051) reference by Mikalef et al. (2018)

According to this theory, firms can gain a sustained competitive advantage by possessing and leveraging valuable, rare, inimitable, and non-substitutable resources and capabilities. The emphasis is on internal factors within the organization, such as human capital, technology, brand reputation, and other tangible or intangible assets, rather than external market conditions alone. The resource-based view helps explain why some firms outperform others and offer insights into how companies can develop and sustain a competitive edge in their respective industries. The concept is subsequently divided into resource-picking and capability-building, with the former involving identifying and procuring strategic resources and the latter focusing on orchestrating and managing these resources to create strategically valuable assets (Mikalef et al., 2018).

In alignment with Resource-Based Theory, many companies have directed their investments toward data analytics tools to harness the increasing availability of data characterized by variety, volume, and velocity. These tools are seen as resources that can potentially enhance the quality of decision-making processes (Ghasemaghaei, 2019; Grover et al., 2018; Mikalef et al., 2018). However, the success rate of these investments has been limited, with only 27% of firms reporting positive outcomes. One critical factor contributing to this limitation is the lack of clarity on the essential conditions required for effective utilization (Ghasemaghaei, 2019).

According to Grover et al. (2018), companies aiming to utilize data analytics tools successfully must possess robust capabilities to integrate, oversee, exchange, and scrutinize large volumes of data in various formats to meet diverse requirements for value creation. In Resource-Based Theory, the company's ability to collect, merge, and effectively utilize its resources specifically tailored for big data constitutes its analytics capability (Mikalef et al., 2018). This capability is essential for generating insights and enhancing the firm's competitive advantage in the dynamic business landscape.

2.3 Big Data Analytics in Banking

The banking sector has witnessed a substantial rise in its investment in data analytics over the years, primarily because of its association with heightened productivity, as noted in studies by (Elia et al., 2022; Gul et al.,202; Gul et al., 2023). As per the findings of Hung et al. (2020), big data analytics is widespread within the banking industry, primarily in the domain of personal banking marketing. The banking industry is divided into two major segments: private banking, which offers services to individuals, and corporate banking, which concentrates on serving corporate clients (Hung et al., 2020). As corporate banking serves as the primary revenue driver for most banks, their utilization of data analytics has primarily been restricted to risk management (Hung et al., 2020). In response to the swift advancements in technology, certain established banks are embracing big data analytics to strengthen their competitive position, enabling them to address challenges posed by FinTech firms more effectively (Gul et al., 2023).

Since banks possess extensive customer demographic, behavioral, and transactional data repositories, big data analytics have demonstrated significant utility in enhancing marketing strategies and their effectiveness in managing risk (Hung et al., 2020). This adoption is particularly prominent in customer segmentation and profiling tasks, predicting product preferences, and forecasting customer attrition (Hung et al., 2020). Numerous banks maintain systematic records of extensive customer data, as Ghafari and Ansari (2018) indicate. Nevertheless, the primary emphasis has been on personal banking when employing big data analytics for marketing purposes (Hung et al., 2020).

Leaders within organizations depend on the quality, pertinence, and accuracy of information when making crucial decisions (Pillay & Van der Merwe, 2021). Pillay and Van der Merwe (2021) additionally note that only 15% of banks in the EMEA region believe that their management primarily relies on analytics for decision-making. Approximately 20% of EMEA bank employees believe contradictory insights from big data analytics can influence their management.

The financial and corporate sectors are heavily invested in developing tools to handle vast amounts of diverse data, which involves significant investments in technology and training for their personnel (Soldatos and Kyriazis, 2022). However, a gap exists in understanding the managerial role in using these tools to extract more sophisticated insights. There is insufficient focus on tracking how these tools influence decision-making processes within these organizations. Furthermore, there is a significant lack of established models or frameworks to assist managers in seamlessly incorporating big data analytics into their decision-making processes (Pillay & Van der Merwe, 2021).

2.4 Decision-making

According to Hernandez et al. (202), decision-making entails the selection of the most optimal solution to a problem with the overarching goal of achieving organizational objectives. Furthermore, among the array of managerial functions, decision-making assumes paramount importance, serving a pivotal role in organizational success by securing a competitive edge, as emphasized by Ghasemaghaei (2019), Gul et al. (2023), and Li et al. (2022). High-performing organizations distinguish themselves from their competitors through their excellence in decision-making, whether by producing high-quality decisions, making expedited choices, or implementing more efficient decision-making processes, as Chiheb et al. (2019) proposed. Recognizing the significance of timely and precise decision-making within organizations is intertwined with the availability of pertinent data and information, which serve as integral components of the decision-making procedure, as noted by Ahmed et al. (2022).

The quality of decision-making pertains to the accuracy and precision of decisions, as assessed through the effectiveness and efficiency of the decision-making process (Li et al., 2022). Following the insights of Shamim et al. (2020), the effectiveness of decisions depends on the accuracy, precision, and reliability of decision outcomes, while efficiency delves into considerations such as time, expenditures, and other resource-related factors. Chiheb et al. (2019) briefly encapsulate the significance of practical decisions, declaring them central transactions in project management and organizational realms. This process is inherently knowledge-intensive, relying heavily on the availability of accurate and pertinent information, as underscored by Ghasemaghaei (2019).

In the contemporary dynamic business landscape, characterized by ever-evolving consumer demands and unpredictable events such as the COVID-19 pandemic, the significance of high-quality decision-making has been magnified for firms, as emphasized by Ghasemaghaei (2019). The adept and successful utilization of datasets, whether small or extensive in scale, significantly influences the caliber of decisions made during an organization's ongoing operations, echoing the insights of Chiheb et al. (2019).

Chiheb et al. (2019) described that decision-making entails selecting actions from various possibilities to achieve predetermined objectives. Incorporating big data into the industrial landscape has ushered in a revolution in decision-making, allowing companies to swiftly identify opportunities and challenges, streamline their operations, and elevate the overall quality of their decision-making, as Li et al. (2022) noted. By harnessing the power of big data, companies gain access to a treasure trove of information, enabling them to make more informed and data-driven decisions. This transformation in decision-making practices has become imperative for companies seeking to remain competitive and adapt to the rapidly shifting business environment.

Highly successful companies outshine their competitors by excelling in decision-making, whether through their choices' quality, speed, or effectiveness (Ahmed et al., 2022). Furthermore, big data analytics is becoming an indispensable component of decision-making processes across various industries (Chiheb et al., 2019). Ghasemaghaei (2019) has uncovered a tangible connection between big data analytics and the quality of decision-making through the exchange of knowledge.

Current investigations into the correlation between big data and the quality of decision-making, as observed by Li et al. (2022), have their limitations. Therefore, grasping the effective utilization of big data analytics to enhance the quality of decision-making remains crucial for a firm's competitive advantage, as underscored by Li et al. (2022). Previous studies have produced inconclusive results regarding the influence of big data analytics on decision-making quality. While some scholars, such as Shamim et al. (2019), have demonstrated a positive impact of using big data analytics on decision-making quality, others, like Ghasemaghaei and Turel (2021), have reported conflicting findings. Furthermore, our comprehension of how big data initiatives can enhance decision-making quality within firms is incomplete, with the precise effects and mechanisms of using big data analytics on decision-making quality remaining elusive (Li et al., 2022).

Hence, companies that bolster their data analytics capabilities by promoting the widespread adoption of big data analytics is expected to maximize the quality of their decision-making (Akter et al., 2016). However, prior research has predominantly treated data analytics capabilities as precursors to a firm's decisions and has explored the direct and indirect impacts of these capabilities on decision-making quality (Shamim et al., 2019, 2020; Awan et al., 2021). Li et al. (2022) observed that data analytics capabilities mediation towards the connection between big data analytics and the quality of decision-making remains an open question.

2.4.1 Data-driven decision-making

The concept of data-driven decision-making (DDDM), as described by Gul et al. (2023), denotes making decisions based on data rather than solely on intuition or expertise. In today's context, with the ongoing evolution of data analytics, data-driven decision-making is increasingly recognized as a potent tool for businesses. It entails collecting and analyzing data to extract valuable insights, which are then shared with relevant stakeholders, ultimately empowering managers to enhance their companies' performance (Gul et al., 2023). In a business landscape marked by heightened complexity due to global expansion and continual innovations, there is a mounting demand for robust decision-making support for business leaders, underscoring the growing significance of data-driven decision-making, as Hung et al. (2020) emphasized. The research conducted by Stobierski, T. (2019) also attests to this by confirming that organizations prioritizing data-driven approaches are three times more likely to report significant improvements in their decision-making processes than those less reliant on data.

The rise of big data as a new source of knowledge has motivated decision-makers in corporations to make faster decisions and to develop their abilities to deal with changes in the environment proactively (Awan et al., 2021). According to Merendino et al. (2018), this has led to decision-making becoming a complicated and increasingly uncertain process in the interconnected world, as it depends on accurate information.

Insufficient emphasis on the importance of data culture and a lack of established practices and behaviors prioritizing data are the fundamental reasons for inadequate strategies (Tabesh et al., 2019). He further asserts that companies that do not possess a culture that prioritizes data may struggle to manage and appreciate their data effectively.

Awan et al. (2021) attest to what Tabesh et al. (2019) have identified from their study, highlighting that the absence of a data culture within organizations often results in a shortfall in data-driven decision-making. This occurs when individuals are not motivated to base their decisions on insights derived from data, instead relying on emotions or preconceived notions. By embracing a data culture, organizations encourage individuals to recognize and utilize patterns in data that support their decision-making processes. Agreeing with Awan et al. (2021), Shamim et al. (2020b) further state that organizations must cultivate a culture centered around data-driven decision-making to lessen their reliance on intuition and gut feelings. Shamim et al. (2020b) additionally state, "Data-driven culture is a key facilitator of data-driven decision-making." It has been contended that to leverage the capabilities of big data fully, organizations focused on data-driven approaches must establish a culture that embraces data-driven decision-making. Without such a culture, managers and decision-makers within data-driven organizations might still rely on gut feelings and instincts to make decisions, subsequently using data primarily to rationalize decisions that have already been made (Shamim et al., 2020b).

While Mikalef et al. (2019a) and Grover et al. (2018) argue that big data analytics can facilitate a data-driven approach to decision-making, while Boldosova and Luoto (2019) further state that for big data analytics to be effective, it is necessary to address the difficulties that managers encounter when interpreting data for decision-making.

According to the statement by Tseng (2023), numerous studies have delved into matters concerning companies' employment of big data analytics for decision-making and have confirmed that enhancing capabilities through data analysis is critical for an enterprise to gain a competitive edge. This agrees with Li et al. (2022), who emphasize that the application of big data analytics enhances the quality of decision-making, and data analysis tools are also used to serve as a mediator. Bahrami and Shokouhyar (2022) also endorse the idea that big data analytics contribute to organizational agility by elevating innovation capabilities and improving information quality, resulting in enhanced overall firm performance.

As stipulated by Awan et al. (2021), previous studies have shown that sharing knowledge has significant implications for decision-making. While other previous studies have established the significance of utilizing big data analytics capabilities for decision-making (Li et al., 2022), there is a scarcity of studies examining how the quality of data interpretation affects the process of making data-driven decisions (Awan et al., 2021; Boldosova and Luoto, 2019). The absence of this understanding hinders organizations from effectively integrating and employing big data analytics in their day-to-day operations.

As Li et al. (2022) highlighted, the existing body of research has predominantly focused on considering data analytics capabilities as a precursor to firms' decision-making processes. These studies have explored data analytics capabilities' direct and indirect impacts on decision-making (Awan et al., 2021; Li et al., 2022). This perspective aligns with Awan et al. (2021), who reference Kristoffersen et al. (2020) and argue that recent research has increasingly emphasized the significance of efficient decision-making in effectively managing the product life cycle. The use of insights derived from data is pivotal in enabling efficient decision-making. Nevertheless, Shamim et al. (2020a) contend that organizations cannot fully harness big data analytics capabilities unless they foster a culture that values data-driven approaches.

For instance, Ghasemaghaei (2019) proposes that an organization's capacity to learn from and apply valuable insights is crucial for effective decision-making. Organizations can confront current challenges and devise innovative solutions by tapping into a wealth of information. Nevertheless, the precise impact of using big data analytics in decision-making is unclear, and there is a gap in comprehending the specific conditions essential for leveraging big data analytics to improve organizational decision-making (Awan et al., 2021; Ghasemaghaei, 2019).

There is a chance that the enthusiasm and overstated assertions regarding the advantages of big data analytics might exert unwarranted pressure on companies to adopt it. Nonetheless, the genuine success of big data projects is contingent on the capacity to generate strategic business value by giving companies a competitive edge in influencing strategic decision-making (Grover et al., 2018). In any organizational hierarchy, the decision-making process is aided by information that can be effectively processed to yield significance (Ahmed et al., 2022). Gathering, analyzing, and presenting large-scale data can assist an organization's management in making well-informed choices regarding the organization's operations and strategy. A culture centered around data is a fundamental enabler of decision-making driven by data (Shamim et al., 2020b).

Despite all that has been argued on data-driven decision-making, Lu et al. (2020) further argue that data-driven decision-making frequently encounters the challenge of dealing with uncertainty or uncharted patterns within continuously flowing data. Systems need to showcase exceptional agility in adapting to the ever-changing landscape of streaming data, often known as "concept drift." Decision-making driven by big data involves stages, including data collection, preparation, analysis, and the actual decision-making process (Shamim et al., 2020b). Gul et al. (2023) also affirm in the study that data-driven decision-making can transform data into valuable information and knowledge that can be employed in the decision-making process.

2.4.2 Big Data Analytics for Decision-making

Participating in decision-making using big data goes beyond merely acquiring access to extensive datasets and conducting analysis, as Shamim et al. (2020b) noted. Big data-driven decision-making can be categorized as creating informational value by harnessing the potential of big data, as described by Elia et al. (2022). Grover et al. (2018) define big data as a powerful source representing a relatively potent resource that can create significant economic and societal benefits and provide a competitive edge comparable to an organization's financial resources and human expertise.

Making decisions driven by big data involves several stages: collecting the necessary data, preparing it, conducting analysis, and ultimately making well-informed and effective decisions (Shamim et al., 2020b), providing invaluable insights that drive meaningful actions (Akhtar et al., 2019). This process of harnessing big data for insights and implementing decisions based on these insights is called big data-driven decision actions, directly influencing overall business performance (Akhtar et al., 2019). However, the adoption of these analytics has significantly increased in the last decade, leading decision-makers to increasingly depend on these analytics and related technologies for decision-making, as opposed to relying solely on their expertise and intuition (Akhtar et al., 2019; Gul et al., 2023; Shamim et al., 2020b).

As a result, in the age of big data, the abundance of data and the subsequent extraction of insights from it are reshaping the global business landscape, facilitating more well-informed decision-making (Gul et al., 2023). Various industries are modifying their business models and approaches, utilizing insights from data to enhance their adaptability and responsiveness to external and internal factors (Awan et al., 2021; Shamim et al., 2020b). This transformation aims to secure a competitive advantage for long-term survival, growth, and sustainability. Through data analytics, business managers can forecast future trends, foresee risks, and comprehend the intricacies of their operations. Therefore, effectively sharing data with managers involved in decision-making is crucial; otherwise, wasting the resources dedicated to working with data will occur. (Gul et al., 2023).

2.4.2.1 Data Quality

In organizations, there is a growing acknowledgment of the pivotal role big data analytics can play in addressing challenges, with data being deemed of good quality when it aligns with intended uses and meets specified requirements (Wang et al., 2019). Data is crucial for companies to formulate strategic choices (Chatterjee et al., 2023; Soldatos & Kyriazis, 2022). Widespread issues with data quality introduce an additional level of intricacy when it comes to utilizing big data for real-time and immediate purposes (Grover et al., 2018). The quality of data is influenced not just by its inherent characteristics but also by the business environment in which the data is utilized, encompassing business procedures and users (Wang et al., 2019).

Numerous scholars have confirmed that ensuring data quality stands as a crucial prerequisite for sound decision-making (Chen et al., 2022; Dubey et al., 2021; Ghasemaghaei et al., 2018), with indications showing that organizations typically rely solely on internal data sources (Jha et al., 2020). Moreover, data generated within the organization originates from outdated legacy systems incapable of adapting to the organization's evolving needs. Analyzing extensive datasets and deriving insights from them can assist the organization in making well-informed decisions and gaining a competitive edge (Jha et al., 2020). These legacy systems cannot be easily replaced, but they must be integrated into big data analytics. According to Jha et al. (2020), "Legacy Data has rigid format issues that do not suit Big Data Applications". Grover et al. (2018) attest to this by stating that organizations must possess robust competencies for integrating, administering, disseminating, and examining large volumes of data in various formats to facilitate different value-generating requirements. This integration should uphold data precision and consistency and be addressed through the organization's chosen Big Data framework and architecture (Grover et al., 2018; Mikalef et al., 2021).

2.4.2.2 Data Integration, Sourcing, and Integrity

Data integration capability refers to the capacity to convert various data types into a format that the data analysis platform can comprehend and evaluate (Wang et al., 2019). Wang et al. (2019) characterized it as the proficiency to convert various forms of data into a data format compatible with the data analysis platform, enabling it to be read and analyzed. Nonetheless, according to Grover et al. (2018), the effective implementation of big data analytics will encounter difficulties without a robust data management framework capable of handling diverse types of big data analyses and promptly providing real-time business insights to users. Therefore, it is vital to integrate extensive and varied datasets from various sources to unleash the potential of big data analytics fully (Soldatos and Kyriazis, 2022).

Wang et al. (2019) attest to this by confirming that big data worth lies in merging and aligning various data sources, encompassing both existing (e.g., legacy system data) and new structured or unstructured data. The diversity in big data introduces complexities, particularly in integrating heterogeneous data from external sources with different time intervals, granularity, and aggregation levels (Grover et al., 2018).

Despite the numerous investments made by companies in big data analytics, companies struggle to fully leverage the potential benefits of these tools (Ghasemaghaei et al., 2018). This is attributed to various factors, including the presence of substandard data, inadequate utilization of suitable data analytics tools, and a scarcity of available analytical skills, as noted by Ghasemaghaei et al. (2018) and Wang et al. (2019). The risk of data inaccuracy is unescapable (Ghasemaghaei et al., 2018; Mikalef et al., 2019b) and is due to inconsistencies in data flow (Ghasemaghaei et al., 2018; Soldatos and Kyriazis, 2022).

2.4.2.3 Data Analytics Insights

The recent rise of big data insights has garnered attention due to its potential to yield profound understanding, ultimately making informed and effective decisions (Shamim et al., 2020b) and providing invaluable insights that drive meaningful actions (Akhtar et al., 2019). Wang et al. (2019) refer to this capability as the ability to impact decisions and behaviors by extensively employing data and various analytical methods. However, without utilizing these insights and translating them into actionable takeaways, they will not hold any value, and no decisions will be made (Awan et al., 2021; Chiheb et al., 2019; Ghasemaghaei, 2019).

These data-driven insights are closely associated with three approaches: descriptive, predictive, and prescriptive insights (Awan et al., 2021). Descriptive insights emphasize the historical and present data relationship to glean task insights, while predictive insights focus on foreseeing potential future outcomes using information from Business Intelligence and Analytics (BI&A). Prescriptive insights refine decision-making to enhance future outcomes (Awan et al., 2021; Ghasemaghaei, 2019).

However, it is crucial to note that these big data insights are not automatically generated by merely applying Big Data tools to data. Instead, they evolve through collaboration between analysts and business managers within existing decision-making frameworks and processes (Akhtar et al., 2019; Hagen & Hess, 2021). Therefore, to maximize the potential of this capability, dedicated big data professionals must collaborate, pooling their individual and collective expertise to make influential decisions (Akhtar et al., 2019). This collaborative effort involves using data and analytical tools to unearth new knowledge (Chiheb et al., 2019). Consequently, organizations need to adapt their decision-making procedures to leverage the potential big data analytics offers (Chiheb et al., 2019).

2.4.2.4 Data Value

Value is commonly associated with a company's economic and financial aspects (Elia et al., 2020). However, it also includes strategic benefits from technological investments that foster innovation, build lasting customer and partner relationships, integrate products and services, and enhance transactional efficiency (Elia et al., 2020). Ghasemaghaei et al. (2018) associate data value with the growing availability of data, which is a driving force for adopting data analytics. Given the evolving nature of big data, experts and researchers employ the concept of the "Vs." to characterize big data value by introducing a threefold definition of big data, encompassing the "three Vs": volume, variety, and velocity, a framework that has gained support from numerous other studies (Elia et al., 2020; Ghasemaghaei, 2019). Apart from the three V's, additional aspects of big data have been discussed, such as the concept of "value," which emphasizes the significance of deriving economic big data. Analyzing data without generating value offers no advantages to an organization, irrespective of the data's size, whether vast or restricted (Chiheb et al., 2019; Elia et al., 2020).

As per Chiheb et al. (2019), Elia et al. (2020), and Nisar et al. (2021), data value refers to the actionable business insights derived from the utilization of big data analytics. These insights can add value in various domains, including improving business processes, innovating products and services, enhancing customer experiences and market position, optimizing organizational performance, and establishing intangible value such as corporate image and reputation (Grover et al., 2018). Essentially, value is derived from big data analytics through collaborative efforts among multidisciplinary team members who share, merge, and integrate their diverse expertise (Akhtar et al., 2019). Recognizing big data as a valuable resource, as emphasized by Grover et al. (2018), becomes crucial for organizations to determine its true accounting, economic, financial, or strategic value. However, assigning a monetary value to data poses a significant challenge for businesses (Grover et al., 2018).

2.4.3 Leadership

A proficient method for guiding organizational members begins with effective leadership (Grover et al., 2018; Shamim et al., 2019). Grover et al. (2018) further state that organizations with leadership teams possessing well-defined big data analytics strategies, clear objectives, and the ability to articulate the business rationale are more likely to achieve success. Attesting to this, Tabesh et al. (2019) further argue that the success of adopting new organizational initiatives hinges on the company's leadership's dedication to the developed strategies and their willingness to offer financial and structural backing throughout the implementation process. Managers must improve the relevant competency dimensions to boost organizational decision-making performance through data analytics tools (Grover et al., 2018). A leadership orientation toward big data can promote collaboration within and between organizations and facilitate knowledge exchange. Furthermore, leadership can cultivate the capabilities needed for effective big data decision-making by fostering a favorable climate (Awan et al., 2021; Shamim et al., 2019).

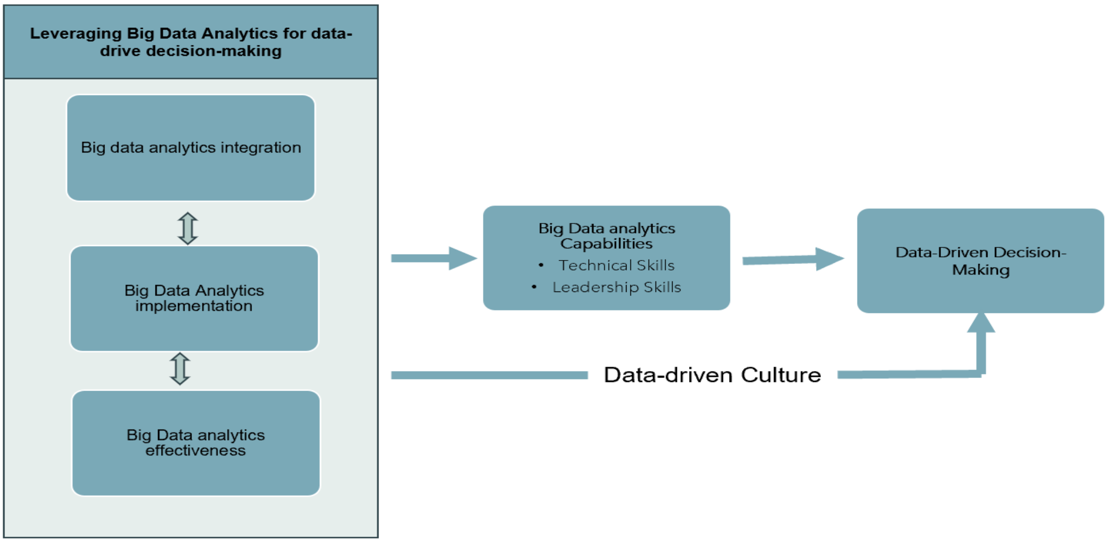
According to Mikalef et al. (2019b), organizations fostering a data-driven culture create a robust alignment between their corporate and articulated analytics strategies. However, the critical factor for achieving this is the emphasis placed by top management on enhancing the significance of big data and analytics in decision-making. Effective endeavors often succeed when driven by a holistic, big data analytics strategy and capable leadership (Grover et al., 2018). In the contemporary landscape, managers increasingly rely on big data analytics for real-time decision-making and the guidance of future organizational initiatives (Mikalef et al., 2019b). Regarding human expertise, the literature acknowledges the necessity for combining technical and managerial skills to extract value from investments in big data. Grover et al. (2018) state that managers using data analytics for organizational decision-making should possess adequate domain knowledge to effectively utilize the tools and interpret the outcomes. To enhance decision-making efficiency and effectiveness, organizations should maximize the utilization of big data analytics tools, facilitating the transition from traditional decision-making practices to data-driven decision-making (Li et al., 2022).

However, Mikalef et al. (2019b) and Shamim et al. (2019) contend that achieving success in big data initiatives is hindered by a significant challenge of unsupportive organizational culture and the presence of data silos that impede access to crucial data necessary for informed decision-making. To bridge this gap, Shamim et al. (2019) state that “attracting the right people with the right skills will be beneficial.” Furthermore, to enhance decision-makers proficiency, they should be able to interpret the outcomes of comprehensive data analysis and grasp their significance (Grover et al., 2018).

2.5 Literature Review Conclusion

The above literature reveals that having strong big data analytics does not directly lead to achieving data-driven decision-making within the organization. Big data analytics staff is imperative to enable companies to make decisions effectively (Chen et al., 2022; Mikalef et al., 2021), leadership that will embrace data-driven culture (Grover et al., 2018) and data quality (Chatterjee et al., 2023; Soldatos and Kyriazis, 2022). This means that even if companies generate valuable data-driven insights through big data analytics capabilities, they still need to take action to benefit from them (Grover et al., 2018). Although data-driven insight is important, it is just one aspect of a company's ability to sense, seize, and reconfigure. Allocating resources to enhance their big data analytics capabilities enables organizations to expedite the generation of insights, acquire a deeper understanding of intricate and swiftly changing situations, establish real-time monitoring capabilities for customers and competitors, pinpoint operational shortcomings and obstacles, and discern shifts in the economic and business environments (Chen et al., 2022).

Figure 2: *Research model framework*



Source: Researcher's own

2.5.1 Research Model Framework

Figure 3 depicts our proposed research model. Drawing from the literature above on leveraging of big data analytics on organizational structure and decision-making, the informed development of the below conceptual framework will explore the multifaceted role of big data analytics in data-driven decision-making, investigating how these analytics contribute to decision processes and examining the influence of organizational culture and leadership on the successful implementation of such tools. The research seeks to uncover factors impacting the adoption of big data analytics, and it strives to offer insights and recommendations for the seamless integration of these analytics into organizational structures and decision-making processes within the South African banking sector.

This research will ask the following three research questions:

- How do big data analytics contribute to the effectiveness of data-driven decision-making?
- How does the organizational culture and leadership impact the successful implementation of big data analytics for data-driven decision-making?
- How can big data analytics be effectively integrated into organizational structures and decision-making processes to enhance data-driven decision-making?

3 CHAPTER 3: RESEARCH QUESTIONS

3.1 Research Questions

This research seeks to identify the factors contributing to the success of big data analytics and understand the conditions under which these capabilities enhance decision-making within the South African banking sector. The study will explore management, technology, talent, and strategic capabilities necessary for effective decision-making while providing insights to the South African banking industry on developing big data analytics capabilities for data-driven decision-making, aligning with prior research urging further examination of the impact of big data analytics on data-driven decision-making.

For this purpose, this study poses the following three research inquiries:

1. *How does big data analytics contribute to the effectiveness of data-driven decision-making?*
2. *How do the organizational culture and leadership impact the successful implementation of big data analytics for data-driven decision-making?*
3. *How can big data analytics be effectively integrated into organizational structures and decision-making processes to enhance data-driven decision-making?*

3.1.1 Research Question 1

How does big data analytics contribute to the effectiveness of data-driven decision-making?

Existing scholarly literature indicates that big data analytics is critical in curating and converting raw big data into valuable information and knowledge for businesses to adapt to change and remain competitive in fiercely contested markets (Dong & Yang, 2020; Grover et al., 2018). Elia et al. (2022) concur with this study, stating that big data has emerged as a catalyst for innovation and competitive advantage, revolutionizing decision-making processes and potentially paving the way for new strategic approaches. To utilize big data effectively for strategic decision-making, a firm needs a range of supportive resources that work together to enhance its overall big data analytics capabilities (Yasmin et al., 2020).

The primary research question sought to gain profound insight into the impact of big data analytics on enhancing data-driven decision-making in the South African banking sector, along with its broader implications for their overall success and competitiveness.

3.1.2 Research Question 2

How do the organizational culture and leadership impact the successful implementation of big data analytics for data-driven decision-making?

Extent literature suggests that insufficient emphasis on the importance of data culture and a lack of established practices and behaviors that prioritize data are the fundamental reasons for inadequate strategies (Tabesh et al., 2019). Awan et al. (2021) attest to what Tabesh et al. (2019) have identified from their study: the lack of a data culture within organizations frequently leads to deficient data-driven decision-making. Agreeing with Awan et al. (2021), Shamim et al. (2020b) further state that organizations must cultivate a culture centered around data-driven decision-making to lessen their reliance on intuition and gut feelings. He further states, "Data-driven culture is a key facilitator of data-driven decision-making." Shamim et al. (2020a) argue that organizations cannot fully realize the potential of big data analytics unless a culture prioritizes data-driven approaches. However, certain researchers argue for knowledge exchange, and managers face challenges when interpreting data for decision-making (Boldosova and Luoto (2019); Grover et al. (2018); Mikalef et al. (2019a).

Research question two explores the intricate relationship between an organization's culture, leadership dynamics, and the effective implementation of big data analytics on data-driven decision-making. It seeks to provide insights into how these cultural and leadership factors can either facilitate or hinder the organization's ability to leverage data-driven insights for decision-making.

3.1.3 Research Question 3

How can big data analytics be effectively integrated into organizational structures and decision-making processes to enhance data-driven decision-making?

Existing literature indicates that the effective integration and utilization of big data resources, referred to as big data analytics capability, have become vital for a company's performance, especially in its ability to meet market demands (Chen et al., 2022). Previous research emphasizes the importance of knowledge sharing in decision-making outcomes (Awan et al., 2021). While existing studies underscore the significance of employing big data analytics capabilities for decision-making (Li et al., 2022), there remains a gap in exploring how the quality of data interpretation influences the process of making data-driven decisions (Awan et al., 2021; Boldosova & Luoto, 2019). This knowledge gap challenges organizations seeking to integrate and utilize big data analytics effectively in their daily operations. Moreover, past research unequivocally highlights the necessity of adopting a comprehensive perspective when assessing the economic benefits of investments in information systems (IS). This perspective should encompass all the underlying elements that enable the proficient and effective utilization of IT as a defining factor in a company's success (Mikalef et al., 2020).

Research question three aims to provide insights into the effective integration of big data analytics into an organization's existing framework and decision-making processes. It addresses both the technical and organizational aspects of this integration and aims to guide organizations in harnessing the power of data to enhance their decision-making capabilities.

4 CHAPTER 4: RESEARCH METHODOLOGY AND DESIGN

4.1 Introduction

This section outlines an overview of the selected research methodology for the study. Information attained from the literature review is used to determine the methodology and identify the population to be used. The chosen approach is exploratory, and the research method, design, sampling, and analysis align with and support the qualitative approach.

4.2 Overview of Research Methodology

The research methodology is a comprehensive plan that outlines how the research would be executed (Saunders et al., 2019), serving as a perspective for researchers to make informed decisions on how to gain knowledge about social phenomena and address research inquiries (Ngulube, n.d.). Scholars generally concur that there are three main research methodologies: qualitative, quantitative, and hybrid, which are a blend of both qualitative and quantitative approaches. For this research study, the approach taken was qualitative, which was an inductive approach used to explore the fundamental causes, symptoms, and consequences of issues and problems to gain a comprehensive understanding (Levitt et al., 2018; Ngulube, n.d.; Saunders et al., 2019).

The qualitative research approach was employed in this study as it aimed to achieve a comprehensive understanding of how big data analytics capabilities could be utilized in decision-making within the banking industry (Ngulube, n.d.) by understanding 'its effectiveness,' 'the key challenges and limitations,' 'impact on the organizational culture and leadership,' and 'integration into the organizational structure.' According to Ngulube, n.d., and Sanchez et al. (2023), when the study aims to investigate an issue and gain a comprehensive understanding of it, the qualitative research approach is an appropriate strategy to implement in the research. A similar study by Awan et al. (2021) employed a qualitative approach to thoroughly examine the connection between big data analytics capability and circular economy performance. The study also analyzed how data-driven insights mediated the relationship between big data analytics capability and decision-making. The qualitative research approach enabled the study to collect substantial non-numerical data and effectively achieve its research objectives. Like Awan et al.'s (2021) research, this study utilized the qualitative approach to gather information and address the research questions.

Qualitative research, an inductive form of research, was employed to investigate the underlying origins, manifestations, and impacts of problems and issues to gain a comprehensive comprehension (Bell et al., 2017). Azungah (2018) defined the inductive form of research as "methods that primarily relied on a comprehensive examination of unprocessed data to formulate concepts and themes, involving a meticulous examination of the data, where codes were assigned to paragraphs or text segments to reveal emerging concepts that were pertinent to the research questions." Kiger and Varpio (2020) further stated that an inductive approach offers a more extensive and comprehensive analysis of the complete dataset, encompassing a broader scope of information. This study adopted an inductive approach to gain a deep understanding of the problem and its challenges (Bryman, 2012). It aimed to identify patterns and connections within broader themes, revealing recurring ideas and concepts from participants' experiences and perspectives (Azungah, 2018).

The research philosophy chosen was interpretivism, as it was vital to understand the factors contributing to big data analytics capability and to explore how this information could enhance data-driven decision-making. According to Sanchez et al. (2023), interpretivism is a paradigm that highlights the significance of comprehending and interpreting individuals' subjective experiences and meanings of social phenomena. Similarly, Bonache (2021) suggested that interpretivism centers on understanding how individuals perceive and make sense of the world and assign significance to their experiences. This philosophical approach also emphasized the study of phenomena within their natural context, providing a suitable framework for obtaining a comprehensive understanding of the subject matter (Bonache, 2021; Saunders & Lewis, 2012). Ghasemaghaei (2019) employed a similar approach by collecting data from 133 managers holding prominent and intermediate positions. The research empirically examined the relationship between data analytics competency and the improvement of firm decision quality by fostering increased knowledge sharing. Ghasemaghaei's (2019) study provided valuable insights for researchers and managers, enhancing their comprehension of the prerequisites necessary to enhance the quality of firm decisions through data analytics. Thus, the interpretivism approach was deemed suitable for this research study since the goal was to gain insights into the factors influencing big data analytics and how these insights could be utilized to enhance data-driven decision-making.

According to Bryman (2012) and Saunders et al. (2019), exploratory research is essential in cases with a relatively novel and unexplored area within the current body of literature. In the context of this study, the requirement for exploratory research emerged from the fact that the subject under investigation lacked sufficient documentation or comprehensive explanation in the existing literature. According to Bell et al. (2017), exploratory research is recommended if a study indicates a gap in knowledge or limited understanding of the specific area under examination.

The study, therefore, utilized cross-sectional semi-structured interviews encompassing open-ended questions. Bryman (2012) and Saunders et al. (2019) defined cross-sectional design research as research where data on the variables of interest is collected simultaneously, offering a balance between structure and flexibility, allowing researchers to delve deeply into participants' experiences and thoughts while still ensuring a consistent approach across interviews (Azungah, 2018). This approach allowed for an in-depth exploration and response to questions surrounding the "how?," "what?," and "why? " in addition to enabling the observation and documentation of the interviewee's non-verbal cues and vocal inflections while aiming to reveal general knowledge regarding big data analytics and its influence on data-driven decision-making within the South African banking industry. By adopting this approach, the research anticipated acquiring valuable findings that would efficiently respond to the initial research propositions regarding using big data analytics to enhance data-informed decision-making (Saunders et al., 2019).

4.3 Population

Bell et al. (2017) and Bryman (2012) defined a population as the entire collection of cases or group members from which a sample could be chosen. Similarly, Bell et al. (2017) and Bryman (2012) defined a population as a comprehensive collection of entities with shared characteristics. For this study, the target population consisted of big data scientist specialists, managers, and directors who are working on or with big data projects within the South African banking sector, as it was these individuals who worked with big data daily and were closest to the challenge of extracting insights from big data to input into organizational decision-making (Bell et al., 2017). Hormozi and Giles (2004) and Dicuonzo et al. (2019) contended that the banking sector produced a significant amount of data that could be utilized to gain a competitive advantage through data mining. Despite substantial access to structured, semi-structured, and unstructured data from financial transactions, this valuable big data reservoir was frequently not fully utilized within the banking sector (Dicuonzo et al., 2019; Pillay & Van der Merwe, 2021). This corresponded to the research conducted by Königstorfer and Thalmann (2020), which revealed that the utilization of big data analytics in commercial banking had not been extensively explored and concluded that big data analytics could be used in all core business areas of commercial banks and could have significant benefits.

The South African banking industry consisted of 36 registered banking entities supervised jointly by the FSCA and the Prudential Authority (PA), with 18 being commercial retail banks, 4 being mutual banks, 5 being cooperative banks, and 13 being local branches of foreign banks according to the South African Reserve Bank Website (2023). The primary focus of this study was on the 18 commercial retail banks in South Africa. Given their large customer base and high volume of interactions and transactions, these banks were expected to possess significant amounts of big data compared to smaller mutual, cooperative, and foreign branches. These individuals would have had access to a substantial volume and variety of data, requiring big data analytics rather than traditional analytical methods. Ghasemaghaei et al. (2018) study intentionally chose the same participants, ensuring that their perspectives would reasonably and meaningfully represent crucial constructs at the organizational level, particularly in the technology and business domains, to address the question in the proposed research model. The study sought to introduce and validate the concept of data analytics competency and empirically evaluate how this competency influences firms' decision-making performance regarding decision quality and efficiency. Therefore, Ghasemaghaei et al. (2018) selected this population because these individuals were relevant to the research problem (Bell et al., 2017; Bryman, 2012).

This aligns with Brymans (2012) additional definition that states a target population refers to the entire set of specific population elements pertinent to the research problem. In studying the influence of big data analytics on firms' strategies, the researchers were dedicated to examining a similar target population. Gnizy (2019) selected the targeted population based on shared characteristics and their relevance to the research topic; therefore, collecting data and addressing the research question could accomplish their research objectives.

4.4 Sampling Method and Size

According to Bell et al. (2017) and Bryman (2012), the appropriate sample size for a study is context-dependent and needs to be determined case-by-case. They further emphasized that in qualitative studies such as this one, there are four non-probability sampling designs to choose from purposive, snowball, convenient, and quota. Therefore, this study used purposive sampling, a selection method where the researcher intentionally chose respondents based on their specific attributes and knowledge that aligned with the research purpose and according to their judgment of the population (Bell et al., 2017). Consequently, the sample consisted of big data scientists, specialists, managers, and directors actively involved in big data projects within the South African commercial banking sector, as they directly related to the research issue (Bell et al., 2017; Bryman, 2012).

This study utilized theoretical saturation to determine the sample size, as suggested by Vasileiou et al. (2018), who stated that the principle commonly employed to determine sample size and assess its adequacy is known as theoretical saturation. According to Bryman (2012) and Vasileiou et al. (2018), this principle indicated that the researcher could stop adding new participants when no significant insights or findings emerged from the respondents. Once this point was reached, where the data from additional respondents aligned with the previously identified themes and did not provide any novel information, theoretical saturation is considered to have been achieved, and therefore, continuing to collect data served no purpose in such cases (Bryman, 2012; Vasileiou et al., 2018). A study by Hagaman and Wutich (2017), which followed the perspective of Guest et al. (2006), indicated that the sample usually reached its saturation when sixteen or fewer interviews had been conducted to identify shared themes among relatively similar groups.

This study further employed purposive sampling (Bell et al., 2017; Bryman, 2012) because it sought individuals with expertise in big data initiatives and outcomes to provide interview insights. According to Bryman (2012), purposive sampling was recommended when interviewees were purposefully chosen based on specific criteria central to the primary research topic. Therefore, the selection criteria were big data professionals (16 data scientists and 16 senior managers in decision-making or fewer until saturation was reached) who had been involved with big data projects and implementations within the South African Retail banking sector. These participants were identified through the LinkedIn platform by searching for individuals with employment titles like Data Science, Analytics Manager, or Chief Data Officer, which provided a database of professionals from diverse industries and their educational and employment backgrounds.

4.5 Unit of analysis

Bell et al. (2017) and Bryman (2012) defined a unit of analysis as the entity or phenomenon a study aims to describe. In this research study, the data were collected individually to investigate the research hypothesis. The big data professionals, including owners, directors, and data scientists, were the focus of analysis in this study. The research explored the relationship between big data analytics and data-driven decision-making through semi-structured interviews with these professionals. The insights provided by their opinions were crucial in achieving the objectives outlined in the previous sections of this paper.

4.6 Research Instrument

The research instrument selected for this study involved semi-structured interviews incorporating open-ended questions. McCracken (1988) asserted that the investigator played a crucial role as an "instrument" in data collection and analysis. According to McCracken, this metaphor held significance as it highlighted the argument that qualitative research objectives could not be solely attained through a limited set of pre-established methodologies. Instead, the investigator had to effectively employ a diverse and unpredictable combination of personal experiences, imagination, and intellectual capabilities.

Bryman (2012) offered further insight into the concept of semi-structured interviews, where the researcher prepared an interview guide containing a list of questions or specific topics to be addressed. During the interview, the interviewees had the flexibility to respond in their own words, providing detailed information and insights beyond the guided questions (Azungah, 2018). These interviews aimed to reveal general knowledge regarding big data analytics and its influence on data-driven decision-making within the South African banking industry. This approach entailed using a predetermined set of themes for discussion, although the sequence of these themes and the questions covered may have varied (Bryman, 2012). Furthermore, additional questions were posed during the interviews based on the context, while certain questions were omitted if deemed necessary, as indicated by Saunders et al. (2019). This method enabled a balance by ensuring data collection consistency while allowing flexibility to explore additional lines of inquiry (Bell et al., 2017; Bryman, 2012).

The data collection and analysis were guided by conducting semi-structured interviews using the predetermined interview guide with a specific group of individuals (Levitt et al., 2018) through telephonic or Microsoft Teams interviews. A prepared interview guide informed by the literature review was used to ensure that each participant was asked about core competencies, culture, values, challenges, and limitations. The interview questions were designed following the three research questions to ensure coherence across the entire research process. The questions in the interview guide were a mix of items that had been adopted, adapted, and self-created (Gill et al., 2008). The structure of the interview guide was intentionally designed to facilitate an open and meaningful conversation about important aspects identified in the literature review. After each interview, participants were allowed to address any important points or ask additional questions that had not been covered (Gill et al., 2008).

This alignment began with the research objectives and literature review and extended to the analysis and discussion of the interview findings, thus maintaining consistency throughout. These identified themes were used to understand how big data analytics impact data-driven decision-making, as the purpose of the study was to gain knowledge rather than produce objective findings.

4.7 Ethical Considerations

Ethical clearance was secured on the 7th of August 2023 (Appendix A: Ethical Clearance Report) from the Gordon Institute of Business Science, following their guidelines before contacting participants. Before commencing the interviews, every individual was once again briefed on the consent paragraph sent before the interview. They were reminded of the voluntary nature of their participation, the assurance of reporting without any personal identifiers, and the recording of the conversation, all of which were undertaken to ensure the ethical collection of data (Saunders & Lewis, 2012). The front page of the interview guide also explicitly stated the commitment to maintaining confidentiality. All participants were proficient in English, eliminating the need for a translator.

Furthermore, information regarding age or race was not collected as it was irrelevant to the analysis. During the interviews, sensitive company information was disclosed, and as a result, no specific details were provided to attribute insights to any particular company. Interview transcripts were subjected to anonymization to maintain the utmost confidentiality.

4.8 Data Gathering Process

Data collection involved obtaining accurate and pertinent data from participants for research purposes (Bell et al., 2017; Bryman, 2012). Four methods commonly used for research data collection were participant observation or ethnography, various types of interviews (face-to-face, telephone, or internet-based), focus group discussions, and document analysis (Bell et al., 2017; Saunders et al., 2019).

This study committed to the online interviews conducted through the collaborative platform of Microsoft Teams. The interviews were scheduled and confirmed via email. The research undertaken by Wea and Dua Kuki (2021), who examined the students' perceptions of using the Microsoft Teams application in online learning during the COVID-19 pandemic, influenced the decision to conduct online interviews. By employing innovative methods and online platforms, the study was undertaken successfully through online interviews that gathered valuable and comprehensive participant data, enabling the researchers to address the research question effectively.

Notes were made During each interview, and all interviews were recorded using the voice recorder feature on Microsoft Teams (Bell et al., 2017; Saunders et al., 2019). Before the interviews were recorded, the interviewer had to request consent from the participants, which was documented through their signed consent forms. A sample of this consent form can be found in Appendix B: Interview Consent Form. Following the interviews, the transcripts from the voice recordings were meticulously transcribed, ensuring alignment with the original recordings. This meticulous transcription process was essential to address any discrepancies that might arise during transcription, thus facilitating a more accurate analysis.

4.9 Data Analysis Approach

Typically, data analysis is associated with qualitative studies, wherein data is transformed and consolidated to extract meaningful information that can generate actionable insights (McCracken, 1988; Saunders et al., 2019). Nevertheless, semi-structured data from qualitative research can also be analyzed using methodologies specifically designed for qualitative research (Gill et al., 2008). According to Bryman (2012), some of the methodologies used for data analysis are thematic analysis, grounded theory, and narrative analysis. In this study, thematic analysis was utilized as the chosen method to extract and identify the expertise and experiences embedded within the opinions of the respondents (Bell et al., 2017; Bryman, 2012). This approach allowed the researcher to uncover and analyze key themes from the participants' perspectives, adding to a comprehensive understanding of the research topic (Bell et al., 2017; Bryman, 2012). Bell et al. (2017) and Bryman (2012) defined thematic analysis as a systematic procedure researchers employ to identify, analyze, and organize data to recognize recurring patterns and themes.

The transcriptions of the interviews were then imported into Atlas.ti, a software tool used for coding and organizing information for qualitative data analysis. Additionally, Microsoft Excel was used both in the coding process and for grouping data to facilitate the thematic analysis. Codes were generated for the themes of the interviews. These codes aided in assessing saturation by observing a decrease in the generation of new codes, which indicated that no significant constructs and themes beyond those already established were emerging. This decrease served as an indicator that saturation had been achieved.

4.10 Research Quality

Reliability and validity were considered to enhance the quality of this study. Without ensuring reliability, the research could not be replicated, diminishing its usefulness. Additionally, without establishing validity, the research could not be trusted, and its outcomes would be considered fictional or imaginary (Bryman, 2012; Saunders et al., 2019). According to Saunders et al. (2019), reliability refers to the degree to which the techniques employed for data collection and analysis yield consistent outcomes. Conversely, validity is characterized by the extent to which data collection methods precisely gauge what they are meant to assess, ensuring that the findings genuinely reflect the intended subject matter (Saunders et al., 2019). Without reliability, the research lacked replicability and consequently held limited value. Similarly, without validity, the research could not be trusted, and its outcomes became fictional or imaginary, rendering it completely useless (Bell et al., 2017; Bryman, 2012).

Qualitative research is characterized by its subjective nature, which could introduce interviewer, interpreter, and respondent biases (Saunders et al., 2019). As qualitative research within the interpretivism philosophy heavily relied on the researcher's interpretation of observations and information, researcher perception bias or preconceived notions could undermine the reliability of research findings (Saunders et al., 2019). To address this, a conscious effort was made to minimize the impact of these biases by maintaining awareness of their potential presence throughout the research process and actively taking steps to mitigate their influence. Furthermore, triangular verification was used as an additional test for reliability and validity by collecting data from one participant in the telecommunication industry to validate the findings.

4.11 Limitations

The semi-structured interview guide employed in this study concentrated exclusively on the constructs identified in the literature review, potentially neglecting the impact of other mediators or moderators on the connection between big data analytics capabilities and data-driven strategic decision-making. Consequently, the use of the framework for conducting semi-structured interviews imposed limitations and potential biases on the data collection and interpretation process, particularly due to the influence of interpreter bias (Bell et al., 2017; Bryman, 2012).

Since the purposive sampling technique was employed, as indicated by Bell et al. (2017) and Bryman (2012), it is important to note that purposive sampling has a limitation in terms of generalization, as its primary objective is to select respondents who possess characteristics that can provide rich information, rather than aiming to generalize findings to other individuals or industries. Therefore, this study's purposive sampling was limited to a specific group of experienced and knowledgeable data professionals in South Africa's banking sector. The findings were not generalized to the entire banking sector in South Africa, internationally, or to other industries. Consequently, the generalizability of the findings was limited to the population from which the sampled data were collected and did not extend to the broader population of the South African banking sector, international contexts, or other industries. Due to the limited scope of organizations included in the semi-structured interviews, it is important to note that the findings of this study may not be applicable or generalizable to other industries or geographical locations. Possible respondent and researcher bias might have arisen from individual opinions and interpretations, such as their understanding of big data and their limited view of the company's big data analytics. The quality of the information gathered during the interviews could have been influenced by the interviewers' lack of experience conducting interviews. The results may lack applicability to other industries or geographic contexts due to the specific focus on the banking sector within South Africa. Future studies could explore additional variables for a more comprehensive understanding. Moreover, the dynamic nature of the data and technology environment suggests that the research's validity may be restricted to a specific timeframe following its completion.

5 CHAPTER 5: FINDINGS

5.1 Introduction

This chapter will unveil the findings from the participants of semi-structured, comprehensive interviews with professionals from the South African banking sector and one from the telecommunications industry. Through thematic analysis of the qualitative interview data, valuable insights were gained into the strategic use of big data analytics on data-driven decision-making within the South African banking industry. Specifically, the exploration delved into the industry's comprehension of harnessing big data analytics and how it can be leveraged in data-driven decision-making.

The findings align with the research questions outlined in chapter 3 to maintain coherence across the report.

5.2 Overview of the sample

Forty-three individuals were approached to participate in the study, with thirty-six candidates via LinkedIn and seven through direct email. Twenty-one of these individuals expressed their willingness to be interviewed. However, four had scheduling constraints and responded with a suitable date after the analysis had commenced, resulting in a final count of seventeen participants available for interviews.

Semi-structured one-on-one online recorded interviews were conducted with the seventeen participants over four weeks, from August 28, 2023, to September 28, 2023. Three interviews were used for pilot purposes and will not form part of the discussions. The fourteen recorded interviews amassed a total duration of 11.6 hours, transcribing 213 pages. On average, each interview lasted approximately 50 minutes. The interviewees were mainly from the banking sector, with only one participant from the telecommunications industry. This participant was used to benchmark the maturity of the data-driven decision-making between the banking sector and the telecommunications industry. Table 1 below shows the distribution of participants contacted (targeted population) and the respondents interviewed.

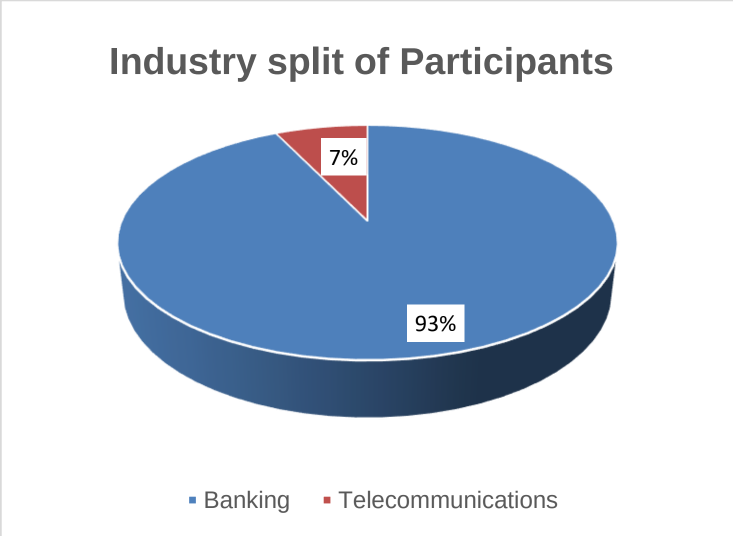
Table 2: *Industry and Position of Participants population and sample*

	Targeted Population	Number of Respondents	Industry
Business Navigator - Data Science Division	1	1	Banking
Chief Data and Analyst Officer	5	1	
Executive: Business Performance	2	1	
Head Advanced Analytics	5	2	
Head Data and Analytics	4	1	
Head of Analytics	8	3	
Head of Analytics	1	1	Telecommunications
Lead Data Scientist	6	1	Banking
Lead Strategic Data Solutions	2	1	
Principal Data Scientist	4	1	
Senior Manager: Analytics	5	1	

Source: Researcher's own

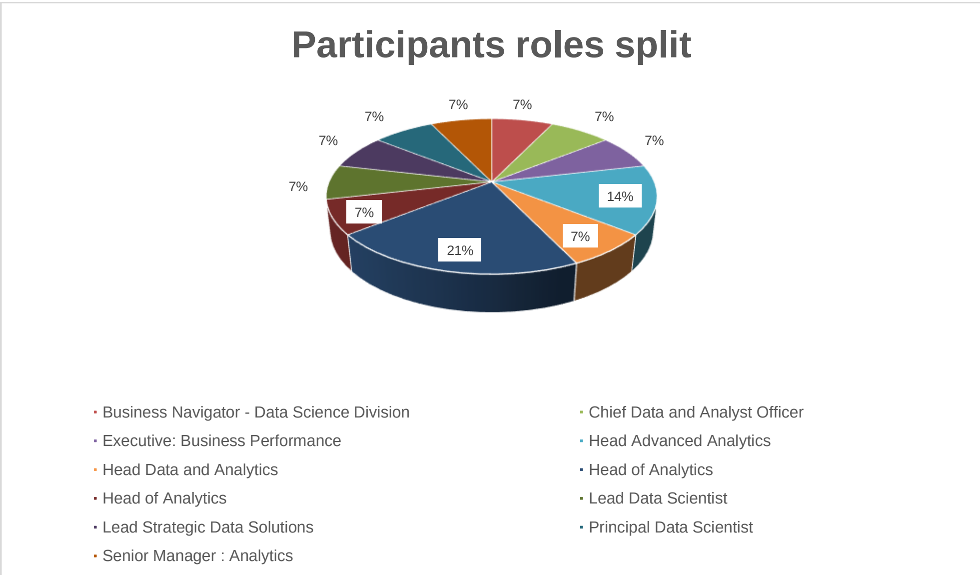
The interviewed participants encompassed a broad spectrum of job roles, spanning from data scientists to Chief Data Analytics Officers. These participants possessed significant expertise and extensive experience in the development, promotion, and execution of data-driven solutions to advance business objectives. Their roles and responsibilities encompassed defining, creating, and implementing data strategies to enhance business performance by driving data-driven decision-making. Figure 3 and Figure 4 illustrate the distribution of Industry and the roles of the participants.

Figure 3: *Industry Split per participant*



Source: Researcher's own

Figure 4*: Participants' Roles Split*



Source: Researcher's own

It is crucial to note that there was no preexisting relationship between the researcher and the respondents, a deliberate measure taken to mitigate any potential bias that could have arisen from such a relationship.

5.3 Presentation of the research findings

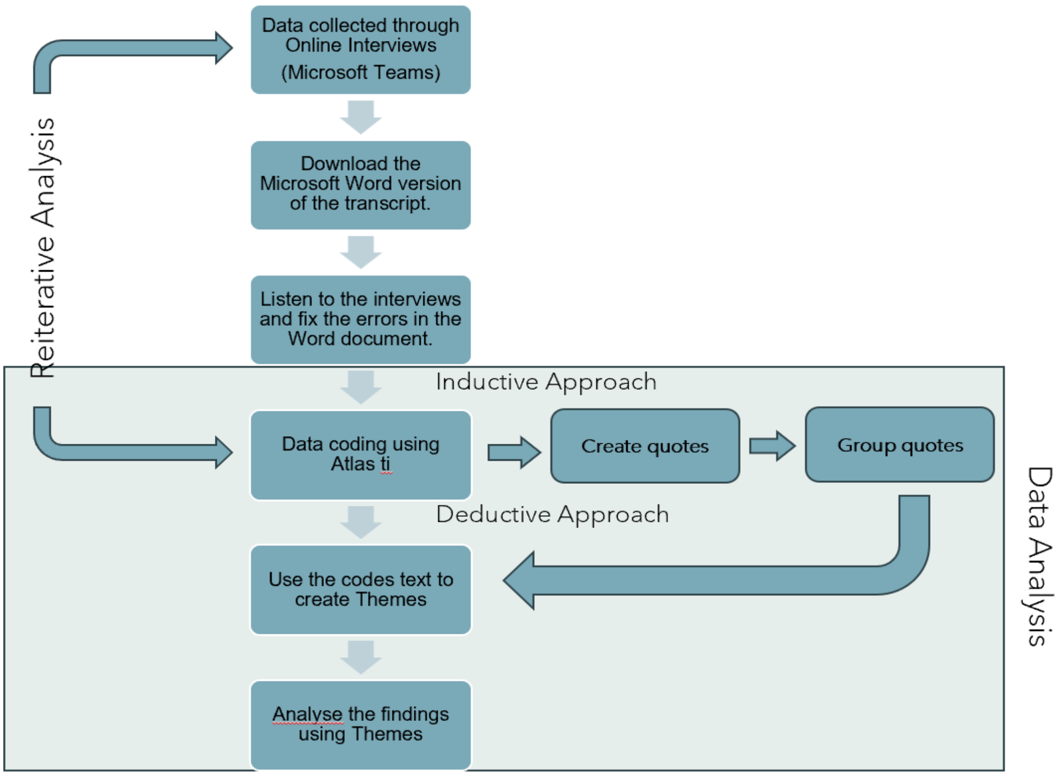
The research process commenced with the researcher immersing herself in the transcribed document from Microsoft Teams. This entailed a thorough review of the responses within the document while also listening to the recording to ensure accuracy and rectify any misspelled information. Following this meticulous data preparation, the document was cleaned and imported into Atlas.ti, marking the initiation of the coding process. During this coding process, the researcher identified and affixed meaningful codes to significant portions of text relevant to the research. Each code encapsulated the essence of the information it represented.

For each respondent, codes were generated next to their responses to highlight key points, and where necessary, the quotations were created. The next step involved thoroughly reviewing the code names to ensure consistency and standardization, especially when different codes represented the same concepts. This iterative process required a detailed analysis of each data line to extract coherent meanings.

Finally, the coding process was completed, and thematic analysis was applied to identify and categorize lists of related codes. The goal was to derive emerging themes or sub-themes that addressed the research questions. This analysis, as outlined by Bryman (2016), entailed systematically exploring recurring words or phrases within the coded data and identifying similarities and disparities to construct coherent categories or themes that closely resonated with the research objectives.

The process flow diagram below, Figure 5, illustrates the development of research themes derived from the codes generated during data analysis, as explained above. These themes outline the qualitative data analysis process to explore how big data analytics contributes to effective data-driven decision-making within the South African banking industry.

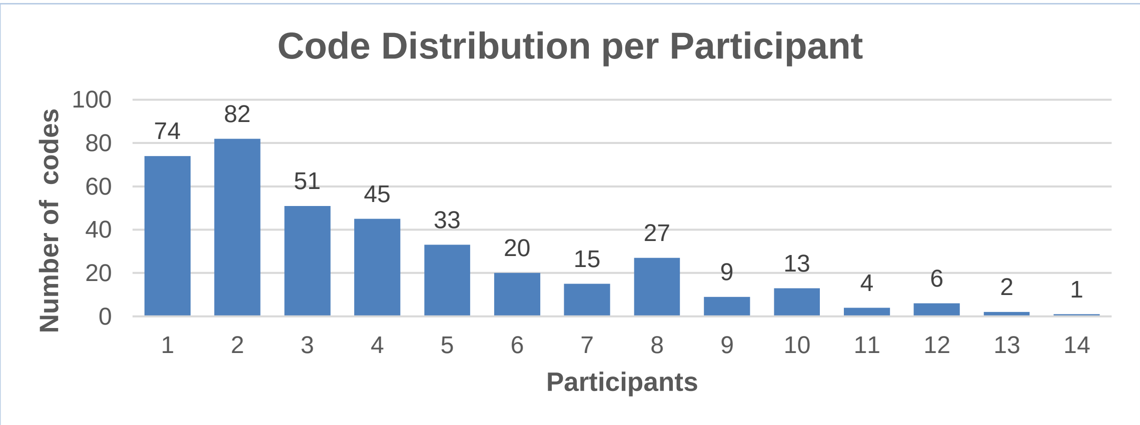
Figure 5: *Process flow diagram for coding*



Source: Researcher's own

The data analysis process revealed that data saturation was attained during the coding of the eleventh interview as the generation of new codes began to decline. In qualitative research, data saturation is typically defined as the point where no additional new codes emerge in successive interviews. The graph below, figure 6 shows the number of codes created for each participant.

Figure 6: *Codes created per participant during data analysis.*



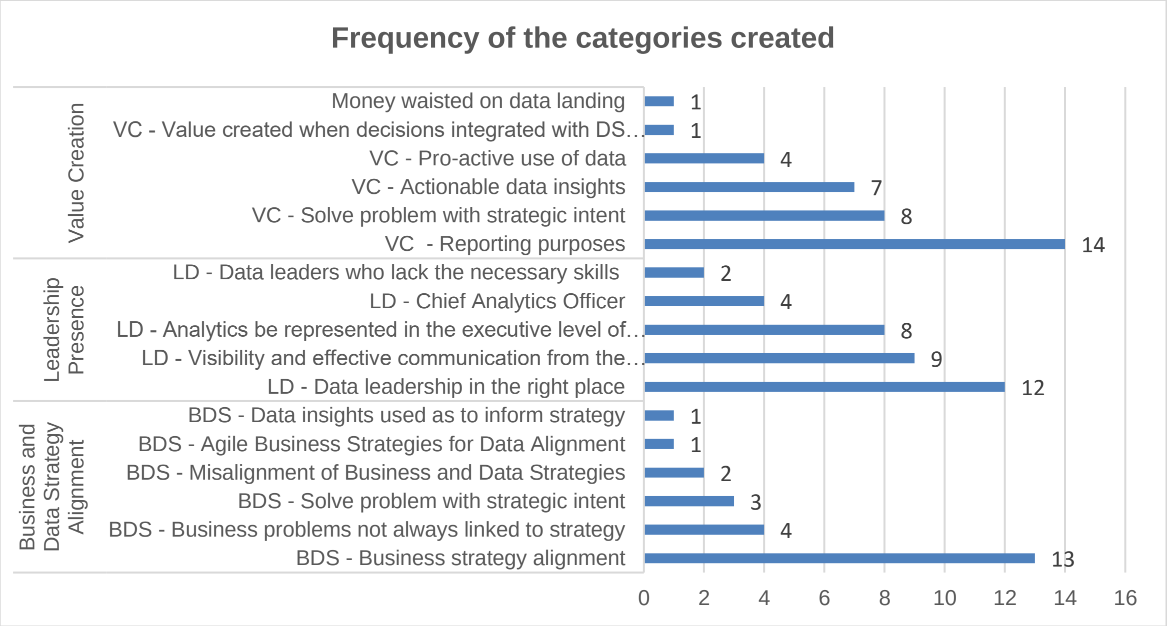
Source: Researcher's own

5.4 Findings for Research Question 1: The effectiveness of big data analytics on data-driven decision-making

Research Question 1: How does big data analytics contribute to the effectiveness of data-driven decision-making?
Aim: This research question aims to delve into the multifaceted role of big data analytics in enhancing the effectiveness of data-driven decision-making in the banking sector. It seeks to understand how big data analytics is practically employed within the organization's decision-making processes while evaluating its perceived value and rationale.

Throughout the interviews, the participants highlighted various elements they perceived as key drivers of effective data-driven decision-making. These elements were organized into constructs and subsequently categorized into three primary themes from the fourteen interviews. Figure 7 below illustrates the themes derived from the Research Question 1 data. More frequent occurrences indicate that many participants encountered or perceived this issue as a challenge to the effectiveness of big data analytics on data-driven decision-making. The following section will detail the first three themes and their respective constructs.

Figure 7: *Frequency of big data analytics effectiveness within the South African Banking sector*



5.4.1 RQ 1: Theme 1 - Business and Data Strategy Alignment

Most respondents underscored the pivotal role of data as both a catalyst and a valuable resource in shaping and propelling business strategy. The prevailing viewpoint among the participants highlights the significance of aligning the data strategy with the intended objectives of the business strategy to harness the full potential of data analytics in advancing business goals.

"…*So I think the key thing, and it is really coming back to an earlier point, is articulating a data and analytics strategy that aligns with the business strategy. And I also think that it is very possible that at this stage, we all want to say we're data-driven organizations to articulate that as a key component of the business strategy"* 5:66 ¶ 11 in P9_LvO.

It is evident that a lack of alignment between the business strategy and the data strategy results in the processing of data that lacks meaningful value. As articulated by one participant: *"…The business strategy must drive data strategy, not the other way around, because then you can end up collecting a lot of amounts to volumes of data that is not useful at all, and even if you look in the organization, how many how much data we have in our side"* 2:34 ¶ 4 in P13_SN_2

In order to underscore the significance of aligning the business strategy with the data strategy, it is worth noting that such alignment enables businesses to utilize data analytics for enhancing sales, effectively managing financial and non-financial risks, and gauging overall business performance.

"…we then use that data to provide or to recommend a product to customers, and we use data to manage risk regulations, both financial and non-financial risk." 12:7 ¶ 3 in P3_DrTN

Emphasis on the fact that organizations are relying on outdated and simple business models for decision-making and believe that there is still a huge opportunity on how big data analytics can be used effectively when aligned with the business strategy.

"…It is effective in the sense that, although there are gaps, we still use it and try and reconcile these different datasets, and then from there, we then use that data to provide or to recommend products to customers, and we use data to manage risk regulations both financial and non-financial risk. And the implications are really effective. We are able to manage customer uh, we are able to track business performance in terms of acquisitions and maybe financial income, we are able to manage risks, and we are able to comply to the regulator. So, it is effective in that manner, but it can be improved in my view." 12:7 ¶ 3 in P3_DrTN

Another participant highlighted the strategy should be agile enough to allow for the current economic industry analysis to be taken into consideration.
"…And what they basically do in there is a review of the existing live credit strategies that are currently in place and look at them and across different metrics to see if they should be kept as is changed or potentially calibrated or something like that, and that's where typically a change that requires and data is the driver would come from because if for instance they say OK, cool, we're seeing that from an acquisitions point of view, our approval rates are looking good, they're trending up". 8:1 ¶ 7 in P12_TR

However, one respondent mentioned that even though there should be alignment between business and data strategy, most of the time, that is not happening.
" …the big thing I had to create a data strategy, but what I notice it's really, really helpful when I get value out of data, we have to make sure that your data strategy actually talks to your business strategy and, in most cases, I can tell that is not happening that way." 2:23 ¶ 4 in P1_AQ

5.4.1.1 Summary of RQ 1: Theme 1 - Business and Data Strategy Alignment

The results from the participants highlighted the significance of aligning a data strategy with the overall business strategy to maximize the effectiveness of big data analytics in decision-making. They emphasize that businesses should recognize data as a vital asset and invest in creating an ecosystem for extracting valuable insights. There is a warning against accumulating excessive, unproductive data when the business strategy does not lead to the data strategy. Participants also stress that reliance on outdated business models is not a sustainable approach, advocating for constant adaptation to evolving customer needs and the changing business environment.

However, one of the respondents held a differing perspective compared to the majority. While most respondents agreed on aligning business strategy with data strategy, this particular individual highlighted the value of potential insights derived from data that could, in fact, steer the organization's business strategy, "*…So there is all of these customer insights, that when working closely with the business will assists the business to understand the targets and actually use these insights to drive the business forward, instead of just using data to complement an existing strategy, letting the data insights drive and shape the strategy itself.* 1:71 ¶ 5 in P6_MvS_1

5.4.2 RQ 1: Theme 2 – Effective Leadership

In Theme 1, a prevalent sentiment was the importance of aligning the data strategy with the broader business strategy. Nonetheless, most participants conveyed that resolving the existing data challenges necessitates a collaborative effort with business leaders from various departments. This collaboration entails gaining a comprehensive understanding of the company's current foremost challenges. The consensus among most participants emphasizes the significance of having data leaders who possess the ability to bridge the gap between data teams and the wider organization. *"…So I think for me if data can have a room even at the strategic level like the insights will easily be seen across cross organization..."* 2:49 ¶ 7 in P13_SN_2

These leaders need to harness the potential of big data analytics more effectively, and they must grasp the intricacies of the decision-making process within the context of big data analytics. Furthermore, they should clearly comprehend the essential organizational elements required to facilitate and bolster the decision-making process centered around big data analytics. *"…is to have a representative coming from the BI and Analytics team in, the executive to be part of the executive membership".* 3:25 ¶ 13 in P5_JX_3

Visibility and effective communication are pivotal in spearheading data initiatives and securing support from senior leaders. *"…I really strongly believe that strategic data value unlock is only possible if you approach it from an organizational perspective*". 5:22 ¶ 4 in P9_LvO

Furthermore, some participants emphasized the importance of appointing the Chief Analytics Officer as a top priority with the hope that the person will focus more on aligning data analytics with the company's requirements and focus on the end users.

"…*will be interesting to see now that analytics officer if you listen to what his name says, it should essentially be somebody that's more focused on the end users the people actually using this data.".* 1:48 ¶ 9 in P6_MvS_1

Another participant articulated that the right leader of the analytics community should actively engage with business leaders right from the outset of their discussions and initiatives. This early involvement ensures a more seamless integration of data-driven insights into the overarching business goals. The person will be a dedicated individual responsible for consolidating everything and ensuring effective delivery. This way, individuals don't find themselves in a situation where they must independently arrive at such conclusions.

"…if you don't get the right leadership in the right place to drive that as an actual strategic outcome, it's a lot more difficult to actually achieve that outcome is that some." 13:31 ¶ 8 in P4_GC

Nonetheless, two participants raised a concern about a prevalent issue in organizations with data leaders who lack the necessary skills to comprehend the value of data. This deficiency can lead to significant investments in data initiatives that ultimately go unused due to ineffective communication and collaboration between data leaders and end-users. They emphasized that there's a need for data leaders who can bridge the gap between the technical and business aspects, serving as effective translators to ensure that data investments are utilized optimally.

"So you need someone who understands the people and who understands the business or understand commercial but and also understand the latest trends around data so that they can become an advocate of that data of that function and have to shape the business in a more sustainable way towards a data-driven" 7:15 ¶ 4 in P11_TM

5.4.2.1 Summary of RQ 1: Theme 2 – Effective Leadership

Participants stressed that addressing current data challenges requires collaboration with business leaders from various departments to comprehensively understand the company's foremost challenges. They also emphasized the significance of having data leaders who can bridge the gap between the data team and the broader organization. Some participants additionally pointed out the necessity of appointing a Chief Analytics Officer as a top priority. This individual would focus on aligning data analytics with the company's requirements and prioritizing the end users.

However, there were concerns raised by two participants regarding a common issue in organizations where many data leaders lack the skills to grasp the value of data. They emphasized the need for data leaders who can bridge the technical and business aspects, acting as effective translators to ensure optimal utilization of data investments.

5.4.3 RQ1: Theme 3 – Value Creation

Another theme that emerged on the effectiveness of big data analysis for decision-making was leveraging value from big data. The preceding section (RQ1: Theme 1) has demonstrated that the bank possesses a wealth of transactional data, which, when harnessed effectively through big data analytics, holds the potential for creating value if aligned with the business strategy. Participants, therefore, highlighted the fact that the banks had come a long way where data was mostly used effectively for reporting purposes, particularly in credit risk and underwriting. Various sources were used to make decisions on credit and insurance applications, and now the organization understands data better.

"…I suppose we have come a long way as an organization in terms of understanding our data and using it in decision-making processes. Of course, when we're talking about credit risk specifically, the vast majority of the decisions that we make our data driven and when we do origination decisions, we really look at the data that we have about our customers, and this is fairly common across banking organizations. We build score cards…". 5:3 ¶ 2 in P9_LvO

"…would say targets for each area in terms of like what they need to achieve for the year, right? And then those particular insights over and above, we will then basically apply them into this particular reporting framework." 3:11 ¶ 3 in P5_JX_3

However, some believe that if the focus can be on how data can help solve business problems rather than solely on the data itself, the value that will allow the business to grow will be created. These projects should, however, be led by the business, and the adoption of insights should be driven by the business question and the value of the action to be taken.

"…Over time, I've come to realize that without obtaining buy-in from the business or stakeholders, customer support tends to vary. This means that producing a multitude of analytics or insights might go unused. However, when these initiatives are driven by the business and its active involvement, especially in terms of buy-in, it becomes more straightforward to extract value compared to the alternative approach". 10:1 ¶ 23 – 24 in P1_AQ

*"…ultimately it's all about identifying what problems we can actually solve and what opportunities we can unpack or exploit with data and yeah..."*1:22 ¶ 7 in P6_MvS_1

"…definitely because what my observation has been that once you expose these insights to business, they are able to take actionable decision that helps grow the bank". 4:2 ¶ 3 in P8_MBid

Two participants added that even though the team solves for the business, the action should be executed.*"…We need to understand the narrative and what kind of closes the loop. If we get this insight, what action are we going to be able to take off the back of that and what is the value of that action"* 5:60 ¶ 8 in P9_LvO. Nonetheless, a participant expressed the perspective that in the domain of data science, the outputs of modeling are seamlessly integrated into established processes and systems. This integration effectively positions the analyst as an integral component of the solution. This distinction sets data science apart from traditional analytics, where the outcomes are smoothly assimilated into daily operations, and actions are initiated without requiring direct intervention. *"…This is also where data science is different. The modeling output gets fed into existing processes and existing systems, so to an extent you almost because you part of that process you almost force action on your result, which is why I really like the data science side of things and you become part of the part of the system part of the solution"* 6:15 ¶ 2 in P10_WB

Some participants emphasized the importance of demonstrating the value of data in small increments and integrating data science and modeling into business processes.
"…So the first one to convince people you actually have to show small incremental bits of value because as soon as you can show a nominal uplift on a small portion of the business, you can then grow it exponentially over time, because then people, it's not just you telling them you can do something, you showing, showing them that you can do it". 13:9 ¶ 4 in P4_GC

The belief that there is still ample opportunity for the organization to leverage data in gaining a deeper understanding of our customers transpired. One participant had mixed feelings about the predictive aspect of their approach. Considering the current macro-level impacts, They emphasize the importance of predicting various pressure points and thresholds that customers can withstand. The participants expressed concern that strategies seem short-term oriented and do not consider a longer time frame, even though it's crucial to plan beyond the immediate future. The participant acknowledges the challenge of relying on historical data for predictions but believes that a more effective utilization of predictive aspects could address this issue, with 70% of their belief in its effectiveness and 30% doubt about its potential. *"…I would say it's effectively used 70%, yes, I do believe 30% it's not effectively used because of the predictive aspect of it. And maybe it's just me not having exposure to the predictive aspects of the area, but in my 5 years, I haven't seen much of that to say."* 8:8 ¶ 8 in P12_TR

Participants felt that even though there is value generated through the insights derived from the analysis, the organization can be pro-active with the data that is accumulated from the customer transaction.
"…To use the data to drive and grow your business, so they need to come up with

answers before the questions are asked". 11:16 ¶ 5 in P2_CS

5.4.3.1 Summary of RQ1: Theme 3 – Value Creation

Participants recognized that effective use of big data, aligned with business strategy, can create value, marking a significant shift from the historical use of data for reporting, particularly in credit risk and underwriting. Some participants stressed the importance of using data to solve business problems rather than just accumulating data. They emphasized the need for such projects to be led by business. Demonstrating the value of data incrementally and integrating data science and modeling into business processes was emphasized to convince stakeholders of the value of data. Participants believed there was untapped potential to gain a deeper understanding of customers through data analysis. There were concerns that strategies often have a short-term focus and do not consider longer time frames. One participant had reservations about the predictive aspect of their approach but believed it could be effective with the right utilization. The opportunity to proactively use data from customer transactions to drive business growth and innovation was highlighted.

5.4.4 Conclusion of Research Question 1: The effectiveness of big data analytics on data-driven decision-making

The impact of big data analytics on data-driven decision-making has emphasized several key factors. These key factors include aligning a data strategy with the overarching business strategy, recognizing data as a valuable asset, and creating an ecosystem for extracting valuable insights. Caution is advised against accumulating excessive and unproductive data without clear alignment with business goals.

Adaptation to changing customer needs and the business environment is seen as crucial. Collaboration with business leaders, effective leadership, and the appointment of a Chief Analytics Officer are suggested to bridge the gap between data teams and the broader organization.

Demonstrating the incremental value of data and integrating it into business processes helps convince stakeholders of its worth. Longer-term focus is encouraged to ensure sustained effectiveness in data-driven decision-making. Finally, proactive data usage from customer transactions is identified to respond to current needs and shape future opportunities.

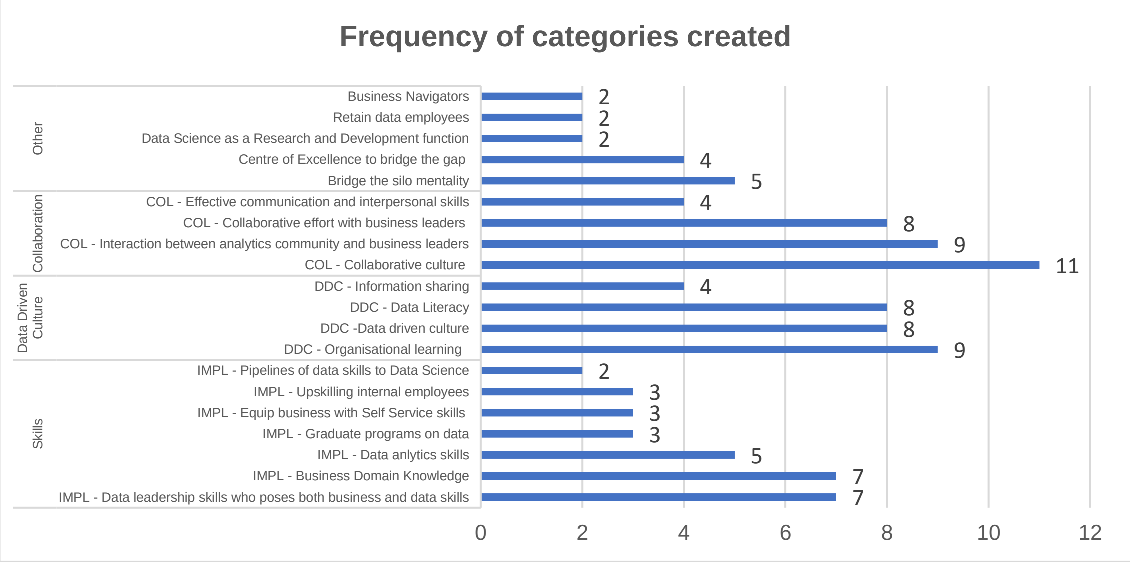
Even though most of the participants agreed that the effectiveness of data-driven decision-making hinges on strategic alignment, recognizing data's value, leadership, value demonstration, and a forward-looking approach to data utilization. One respondent mentioned, "*Effective use of big data analytics really depends on the audience.*" 6:1 ¶ 2 in P12_TR . The participant further highlighted that the effectiveness could be estimated to be approximately 60-70% of the time; when analytics are conducted and conclusions are presented, the response varies. In some instances, a significant portion of the work results in conclusions, but the subsequent actions taken may not always be visible. However, the level of responsiveness greatly hinges on the audience.

5.5 Findings for Research Question 2: Effective implementation of big data analytics on data-driven decision-making

Research Question 2: How does your organizational culture and leadership impact the successful implementation of big data analytics for data-driven decision-making?
Aim: Research question two aims to explore the intricate relationship between an organization's culture, its leadership dynamics, and the effective implementation of big data analytics in the banking sector. It seeks to provide insights into how these cultural and leadership factors can either facilitate or hinder the organization's ability to leverage data-driven insights for decision-making.

Throughout the interviews, the participants highlighted various elements they perceived as key drivers that could assist in implementing big data analytics into data-driven decisions. These elements were organized into constructs and subsequently categorized into three primary themes from the fourteen interviews. Figure 8 below illustrates the themes derived from the Research Question 2 data. More frequent occurrences indicate that a larger number of participants encountered or perceived this issue as a challenge to the effectiveness of big data analytics on data-driven decision-making. The following section will detail the first three themes and their respective constructs.

Figure 8: *Frequency of the implementation of big data analytics within the South African banking sector*



5.5.1 RQ 2: Theme 1 – Essential Skill Sets for Effective Implementation of Big Data Analytics

The respondents' overall perspective is that banks have accumulated the necessary resources to create a unified and well-managed data source for various purposes, as demonstrated in research question 1 findings. At the same time, recognizing that banks are making strides in leveraging these capabilities to establish a comprehensive data ecosystem, which in turn supports informed decision-making and reporting. The respondents emphasize the essential need to equip employees with proficiency in both data and business skills, an imperative step towards effectively driving the implementation of data-driven decision-making. Furthermore, these participants highlighted the necessity of bridging the language and understanding gap between data specialists and business professionals. Ultimately, it equips data scientists and analysts with value-driven skills and encourages data professionals to understand and communicate in the language of business. This approach is seen as crucial for successful data-driven decision-making and the generation of business value. *"…And so equipping data scientists and analysts with the skills to be able to think from that business value driven perspective as they are going through their work, I think is something that's important focus on."* 5:61 ¶ 8 in P9_LvO

"…Data should be able to generate revenues just like any other products and services that the business provides, meaning that a person, a data professional, is not only supposed to be a specialist but also understand business, be able to translate what you

say in data to business because there is a need to bridge the gap between business people and us [data scientist or analyst]" 4:12 ¶ 6 in P8_MBid

Some acknowledged that banks are still in the process of cultivating the competencies to fully unleash the potential of data while navigating the highly competitive landscape for data skills in the market and addressing the importance of implementing effective strategies for retaining these skilled resources.*"…So my experience has been, I mean first just talking about the skills of people that we actually have the most amazing data analytics skills in the country. We have fantastic professionals, but they're spread quite thin, so we've got a number of organizations, everybody's talking data and analytics."* 5:18 ¶ 4 in P9_LvO

"…Yeah, so and really focusing on some retention strategies and that I said there is so much competition in the market for data skills." 12:33 ¶ 7 in P3_DrTN

To address this, some participants emphasized upskilling internal employees, allowing them to adapt and contribute effectively to data-related tasks. Encouraging self-service and upskilling within the workforce is essential for a data-driven culture.*"…upskilling internal employees who are interested in career change"* 12:31 ¶ 7 in P3_DrTN

"…And I'm saying data is not only limited to data specialists. We should organize our data in such a way that anyone with the business can just go and design their own report and get the inside that they want." 4:22 ¶ 10 in P8_MBid

Two participants delved into the considerable influence of the emerging field of data scientists within the realm of big data. They highlighted why they have a strong inclination towards data science as it excels at retaining the outcome within the process. One further stated that it begins with a profound analysis stage, enabling a deep comprehension of the problem and highlighting how it paves the way for a scientific or modeling approach to problem-solving. However, they also pointed out a critical issue - the current shortage of data science and analytical skills, which poses a hindrance to effective data exploration. To address this shortage, they proposed the creation of educational pipelines from universities to bridge the gap in data skills. *"…We recommend that business create pipelines of data skills right from the university, right from the grassroots, and we have seen most universities ever actually come up with curriculums that either focus direct space specifically on data"* 12:29 ¶ 7 in P3_DrTN. At the same time, one participant believed that the Centre of Excellence could bridge the gap within the organization. *"…Umm, thinking some kind of a knowledge center or? Other areas, called them Centers of Excellence, right or competency centers where in that you have a strong* *training capability and a lot of people actually overlooked that and it's very important."* 11:11 ¶ 4 in P2_CS

However, seven participants emphasized the importance of business skills as the most crucial skill, as it is a solid grasp of business understanding. The participants continued by saying it is essential to have individuals with strong data skills who also comprehend the potential of data. This understanding should extend to the intricacies of the business itself. *"…I think the biggest skill for me is probably business understanding. So, you need people with sufficient data skills. It kind of knows what's possible with data. Umm, I think to understand the business better".* 1:54 ¶ 7 in P6_MvS_1

Another respondent emphasized the need to improve business and data literacy, mentioning that the banking sector offers short courses designed to teach the basics of risk management and related processes, enabling individuals to understand discussions about controls and risk assessment better. However, the ultimate goal should be to bridge the knowledge gap and promote alignment between business and data literacy within the organization. *"… there are short courses as well that are designed specifically for risk. What is risk management and what is the risk management process? Just understanding the basics to an extent that when someone talks about controls or talks about monitoring or assessing risk, you kind of understand already. So, reaching the gap, or should I say elevating both business and data literacy, is something that we continue to do because it helps everyone to be on the same page."* 12:38 ¶ 8 in P3_DrTN

5.5.1.1 Summary of RQ 2: Theme 1 – Essential Skill Sets for Effective Implementation of Big Data Analytics

In summary, the respondents' perspective highlights that banks have acquired the resources needed to establish a well-managed data source for various purposes. While they recognize progress in leveraging these capabilities to create a comprehensive data ecosystem, they also acknowledge the ongoing development of competencies to utilize data fully. The intense competition for data skills and the need for effective retention strategies are underscored.

The participants emphasize upskilling internal employees and fostering a self-service culture to address these challenges. They stress the importance of bridging the gap in language and understanding between data specialists and business professionals, promoting value-driven skills, and encouraging data professionals to communicate effectively in business terms. In addition, some participants suggest creating educational pipelines for data skills, starting from universities, while others propose establishing Centers of Excellence or competency centers within organizations to bridge the skills gap.

5.5.2 RQ 2: Theme 2 – Data-driven culture

Most participants attest to the fact that years ago, the culture around data in the organization was not very strong. However, they are now witnessing a significant shift towards a more data-oriented culture, with the organization's top leadership enthusiastic about data. These participants mentioned that the leadership understands its importance and is willing to invest in data-related initiatives. Some even highlighted that recently, they have seen a substantial focus on data, with key initiatives being introduced to incorporate data into everyday banking operations. One participant stated that the leadership fully supports the initiatives and agrees on the necessary investments, leading to a significantly improved data culture compared to a decade ago.
"Actually really improving, and we're seeing a lot of buy-in, I mean, for the fact that you actually get to a point where business and stakeholders are actually coming up with data use cases, it tells you that the data culture is shifting and in the past I mean I've been in the data flow for most of my career and in the past people will then just come to you and say tell me what my business problems are." 10:18 ¶ 40 in P1_AQ

While there is an acknowledgment of the improvement of business and stakeholders on actively generating data use cases to demonstrate a notable shift in data culture, most respondents felt that there is still a shortage of data skills, as highlighted in RQ 2 – Theme 1 (Skills Sets for Effective implantation of Big Data Analytics), and resources are limited, particularly in the realm of data skills that could enhance the data-driven culture within our organizations. Recognizing the imperative to equip the internal employees with the skills necessary for data-driven decision-making, some respondents from two different banks mentioned that their organizations have proactively initiated a range of programs like data literacy, crafted for custom data courses that specifically cater to their organization's needs, particularly in areas like non-financial risk. This strategic move aligns with the widespread demand for data expertise and serves to bolster data literacy throughout the organization. *"…as data leaders, we have put in place programs that help specifically around data literacy and trying to get everyone to move it the same wavelength and speak the same language".* 12:74 ¶ 8 in P3_DrTN

One participant provided a detailed insight into their approach. They underscored their strong commitment to enhancing data literacy, particularly on the data front. At the conclusion of educational courses, they employ assessments to gauge participants' comprehension, effectively measuring the impact of their interventions. In addition, their evaluation extends to conducting a comprehensive data maturity assessment across the entire organization. This assessment encompasses multiple facets, encompassing an understanding of data, the value attributed to data, alignment with the organization's data vision, data governance, the processes involved in data management, cultural aspects, and the provision of opportunities for employees to enhance their data skills. Furthermore, they delve into the organization's grasp of how technology empowers data utilization and informs decision-making. "*… we've got an assessment to test the understanding, and that's where you can then see how effective this intervention is. But as part as another way of, checking the effectiveness of that is also doing a data maturity assessment in the organization where you kind of like access across the organization"* 12:75 ¶ 9 in P12_TR

One of the participants shared an important observation that their organization's primary objective has been to actively involve all stakeholders in their data journey. To accomplish this, they have implemented a variety of initiatives, including organizing master classes, and developing data-focused blogs with efforts designed to equip individuals with essential data-related skills. The participant highlighted a significant challenge in the form of hesitance and resistance among some individuals when it comes to embracing a data-driven culture. This resistance is often attributed to a lack of understanding of the data culture's importance and benefits. *"…we ran a lot of master classes and data blogs just to make sure that we have skilled people on data and because one of the things that we've realized is that some people are shy or are resistant in adopting this data culture because they don't understand..."* 10:4 ¶ 37 in P1_AQ.

A noteworthy observation from two participants revolves around senior leadership's accountability concerning data quality. The extent of accountability is closely linked to the influence of data on the organization's financial statements. Currently, issues that don't directly impact the senior level's income statement tend to receive less attention. In contrast, matters that directly affect the bottom line become significant concerns. The participant suggests the need to establish a method for quantifying data's impact on financial statements, such as the income statement or balance sheet. They propose that penalties resulting from mishandling data, reflected in the income statement, would lead senior leaders to take data management more seriously. From the participant's perspective, without this form of measurement, the organization's recognition of data as a valuable asset may remain a distant objective. Moreover, this type of measurement could aid in dismantling existing silos and ensuring that the data strategy aligns seamlessly with the overarching business strategy. Employing financial metrics, such as the income statement, for measurement could serve as a pivotal starting point. This is exemplified by the case of new business ventures, where the appeal lies in their direct influence on the net interest margin, a critical financial indicator. *"…find a way to make sure that data is measured in the income statement or balance sheet, and because if that really, let's say if poor management of data would result in some penalties on their income statement… hat is not done then seeing data as an asset in the organization will still take a long time to realize that."* 2:41 ¶ 5 in P13_SN_2

Two of the participants shed light on a critical challenge related to the absence of a data-driven culture within their organizations. One of the participants' insights centered around the essential need for data domain expertise. According to the participant, the most influential individuals in the data realm are those with deep, domain-specific data knowledge. This proficiency is not limited to data scientists, data engineers, or other data professionals but extends to anyone who comprehends the intricacies of data within a particular domain. The participant emphasized that individuals working in the field of business intelligence (BI) often acquire substantial data knowledge. However, the persisting challenge stems from organizations' failure to nurture data domain experts. Without these experts, organizations struggle to access the right data seamlessly, leading to significant difficulties in generating high-quality reports. This, in turn, necessitates a time-consuming process of seeking out individuals who can offer the required insights. *"…And so, the biggest problem is that we are lacking data domain knowledge … I would say it is the most powerful attribute, the most powerful person in data is someone that has domain knowledge of data..."* 14:61 ¶ 10 in P7_NY_4.

According to the second respondent, a key contributing factor to this absence is a need for more understanding of the significance of a unified perspective on data. They elaborated further, emphasizing that this issue is primarily rooted in a pervasive misunderstanding of the importance of a consolidated data view. The participant noted that this cultural challenge is closely intertwined with the existence of silos within the organization. Within these silos, individuals tend to be territorial, often driven by a desire to maintain control over their specific areas, sometimes at the expense of the broader organizational objectives. Additionally, the respondent highlighted that concerns related to data confidentiality play a role in hindering the development of a data-driven culture.

In certain businesses, there is a reluctance to expose sensitive data to everyone, which is a legitimate concern. However, the participant pointed out that there are alternative strategies, such as data masking, to ensure the security of sensitive information.
"…it talks to culture, which is the lack of understanding of what it means to have a consolidated view of data… people also want to be territorial, and they want to control their space ….someone would say, I've got my budget, I don't need your assistance or your help…" 12:73 ¶ 6 in P3_DrTN.

Yet another participant expressed the need to implement the right programs to elevate data visibility and position it as a valuable asset within the organization. *"…put the right programs in place? How do you create the right visibility so that you can get people to understand that everyone plays a role in data? Because if you can get everyone to become a data practitioner or someone that stands up for data., the only way you create that data-driven organization is when someone integrates data into everyday business processes."* 13:35 ¶ 9 in P4_GC

However, one participant mentioned that in her observation, it appears that their organization is still in a phase of resistance when it comes to data capabilities within the bank. Some business units continue to make decisions that are not rooted in facts, insights, or data but rather rely on their past experiences. The participant further made an example, saying that those individuals may choose solutions that worked for them in previous companies or are common in the market without necessarily considering if they are suitable for their bank. This stage, which she calls "data denial," suggests that some individuals still believe they can make decisions independently of data-driven insights. *"…I think what I've observed is that they still, but we are still in a denial phase in our data… so what I've observed is that there is that data denial, we call it data denial stage. When people are feeling like they can still make decisions outside the effects…"* 4:28 ¶ 4 in P8_MBid

5.5.2.1 Summary of RQ 2: Theme 2 – Data-driven culture

Organizations have significantly shifted to a more data-oriented culture. Top leadership now recognizes the importance of data and invests in data-related initiatives. This change is reflected in more stakeholders actively generating data use cases, signaling a clear shift in data culture.

However, despite this transformation, organizations still have a notable shortage of data skills. Some proactively address this by implementing targeted data literacy programs and custom data courses to improve their workforce. To ensure the effectiveness of these initiatives, organizations actively assess their impact. They measure participant understanding through assessments and perform data maturity assessments to evaluate various aspects of data knowledge, governance, and culture.

Senior leadership's accountability for data quality has also been emphasized. Participants suggest that measuring data's impact on financial statements, like the income statement or balance sheet, would encourage leaders to take data management more seriously.

One common challenge in the absence of a data-driven culture is due to a lack of understanding, which is often exacerbated by silos within organizations. Data confidentiality concerns in some businesses also hinder the development of a data-driven culture. Participants also underscore the need for data domain expertise. The absence of these experts leads to difficulties in accessing the right data for quality reporting. Efforts to elevate data visibility and encourage a culture where everyone plays a role in data are emphasized. Integrating data into everyday business processes is seen as crucial for cultivating a data-driven culture.

5.5.3 RQ 2: Theme 3 – Collaboration

Collaboration emerged as a significant and recurring theme in discussions about the adoption of data-driven decision-making within the organization. This theme underscores the importance of fostering a collaborative culture that enables leadership to contemplate how to establish a leadership structure within an organization that supports more expansive and forward-thinking approaches, ensuring that the data analytics skills are structured effectively for optimal utilization. *"I think it has to be a collaborative culture, and I think that enables then and making sure, for example, that we have our skills and data analytics skills set up in a way that enables us to make the best use of them because they are very, very scarce skills and in the industry and it also enables us to think about how we set app leadership structures within an organization to support that broader thinking"*. 5:26 ¶ 4 in P9_LvO

Most participants highlighted the significance of several skills, particularly understanding effective communication and interpersonal skills. They pointed out that while having individuals with data skills who possess some level of business understanding is essential, it is equally crucial for these individuals to excel in communication and collaboration. This combination of skills is seen as a driving force behind successfully identifying and capitalizing on valuable opportunities, as it ensures that insights are effectively conveyed and that collaboration across the organization is seamless. *"…So business understanding probably together with kind of communication and people skills, because sometimes even when you've got people with a data skills and they understand the business, maybe a little bit and then identify maybe a really good opportunity if they can't communicate, and they can't work with other people in the business then it's never really gonna go anywhere."* 1:26 ¶ 7 in P6_MvS_1

The participants stress the significance of analytics professionals immersing themselves within the business, whether in roles that directly support analytics or in non-analytics positions. This hands-on experience equips them with a profound understanding of the organization's inner workings, including how it interconnects. Consequently, they can deliver analytics solutions tuned to the specific business context. *"…that we will normally work with the data domain managers that will be coming from this particular product houses to basically leverage all the data that they deem to be an accurate view as an example"* 3:14 ¶ 5 in P5_JX_3

One participant emphasized that alignment with business needs is a top priority, and regular conversations with business leaders are essential to guarantee that every project or initiative meets these needs effectively. *"…any solution that gets put forward for implementation and has to go through a business, sign off and business engagement process and before you put it out there and it forces the interaction between the analytics community and their business leaders."* 5:62 ¶ 10 in P11_TM

One participant highlighted the need to create a sense of community among data scientists and analysts and the business as vital. The participant further elaborated that doing so will foster the visibility of the work across different areas and encourage conversations on leveraging these insights while aiming to eliminate the need for personal relationships as a prerequisite for collaboration, as it is not the most effective approach. *"…The collaboration needs to happen irrespective because as data people will just get technical sometimes and not understand the business world, whereas we should understand the business world as well".* 4:29 ¶ 12 in P8_MBid

Nonetheless, another participant recognized collaboration as an undoubtedly prevalent challenge that organizations must confront, emphasizing its significance. This participant pointed out that many organizations operate with a silo mentality, where different business units compete against each other. The participant explained that organizations should adopt a more comprehensive perspective when profiling their customers, ensuring that products are contextually relevant. This approach involves offering the most suitable product based on each customer's unique needs rather than engaging in a race to sell as many credit cards as possible. Such an approach demands a strategic focus on the organization's overarching objectives and how to serve its customers best beyond duct level.

"…In many banking organizations, including our own, the structure has evolved begins as a specialized business, with different components added gradually. The organizational culture, systems, and data are typically compartmentalized, with a focus on individual areas and their performance, rather than on collaboration or sharing data for added value." 5:24 ¶ 4 in P3_DrTN

5.5.3.1 Summary of RQ 2: Theme 3 – Collaboration

In summary, the discussions emphasize the importance of collaboration, skills, immersion in the business, alignment with business needs, and creating a collaborative community in the context of data-driven decision-making. The challenges of siloed organizational structures are also acknowledged as impediments to effective collaboration and value generation.

5.5.4 Conclusion of Research Question 2: Effective implementation of big data analytics on data-driven decision-making

Organizational culture and leadership significantly influence the successful implementation of big data analytics for data-driven decision-making. The summarized results reveal interconnected themes that highlight this impact. Leadership recognizes the shortage of data skills and takes proactive measures to address it, including upskilling employees, promoting data literacy, and encouraging value-driven skills. They invest in data-related initiatives and assess their impact, demonstrating a commitment to building the necessary competencies within the workforce. Moreover, leadership acknowledges the importance of data and actively fosters a cultural shift toward valuing data as a strategic asset. This shift is reflected in increased stakeholder involvement in generating data use cases, signifying a commitment to nurturing a data-driven culture.

Collaboration emerges as a pivotal theme in data-driven decision-making. The organizational culture and leadership are in supporting leadership structures that encourage collaboration and forward-thinking approaches. Effective structuring of data analytics skills is vital for optimal utilization, with collaboration facilitating a broader perspective. In addition, participants emphasize the significance of skills such as business understanding, effective communication, and interpersonal skills within the data analytics field. Leadership acknowledges the value of these skills in identifying opportunities and facilitating collaboration across the organization.

Fostering a sense of community among data professionals and the broader business is essential. This approach encourages visibility of work, promotes collaboration, and seeks to reduce the reliance on personal relationships as a prerequisite for effective collaboration.

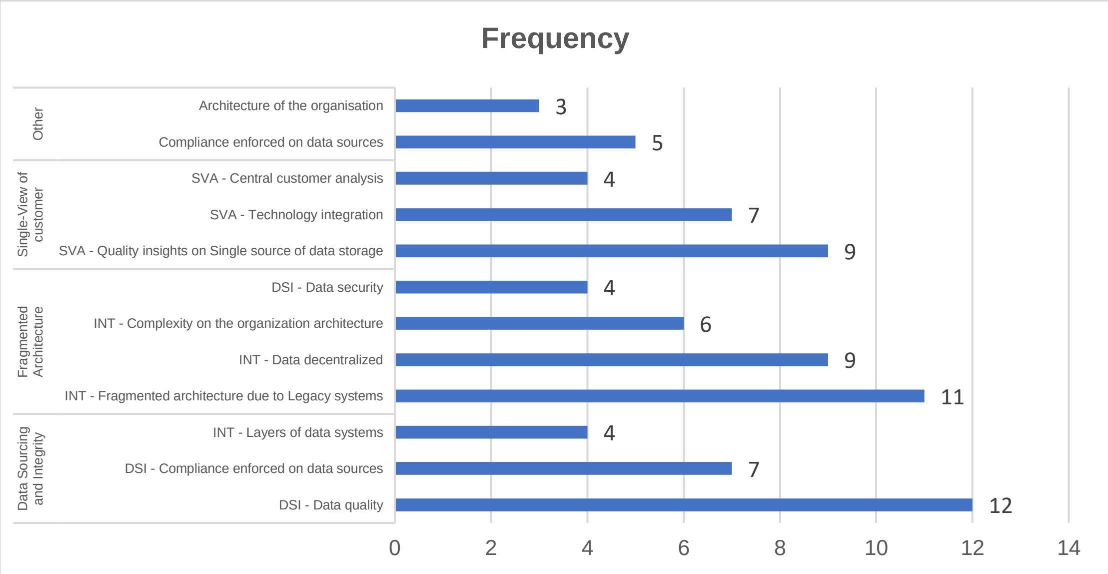
However, some participants acknowledge that collaboration can be challenging due to siloed organizational structures. Overcoming these challenges is vital for successful data-driven decision-making, as siloed structures prioritize individual area performance over collaboration and data sharing.

5.6 Findings for Research Question 3: Integrating Big Data Analytics within existing organizational structures.

Research Question 3: How can big data analytics be effectively integrated into existing organizational structures and decision-making processes to enhance decision-making?
Aim: Research question three provides insights into the effective integration of big data analytics into an organization's existing framework and decision-making processes. It addresses both the technical and organizational aspects of this integration and aims to guide organizations in harnessing the power of data to enhance their decision-making capabilities.

Throughout the interviews, the participants highlighted various elements they perceived as key drivers that could assist in integrating big data analytics into data-driven decisions. These elements were organized into constructs and subsequently categorized into three primary themes from the fourteen interviews. Figure 9 below illustrates the themes derived from the research question 3 data. More frequent occurrences indicate that many participants encountered or perceived this issue as a challenge to the effectiveness of big data analytics on data-driven decision-making. The following section will detail the first three themes and their respective constructs.

Figure 9: *Frequency of the challenges the participants foresee in integrating big data analytics into the South African Banking sector decision-making.*



5.6.1 RQ 3: Theme 1 – Data Sourcing and Data Integrity

Respondents offered diverse perspectives when asked about integrating big data analytics into their organizational framework. One respondent's response was, "*I don't think the effect of big data in terms of having access to all of the information and considering everything has been embedded in all areas in the business.*" 1:11 ¶ 4 in P6_MvS_1

While some highlighted the difficulty in sourcing data within their specific environments, others pointed out issues related to data quality during analysis. However, a majority of respondents shared their concerns about the hindrances posed by legacy systems, which impede the integration of data sources. *"…you know our banks are very legacy, there are hundreds, they are over 100 years old. So, you still have legacy systems that you're trying to work around to be able to build that view and so forth."* 7:19 ¶ 3 in P11_TM

While other respondents felt that the banks' data integrity is somehow questioned because the industry does not treat data as an asset, another respondent conveyed the importance of instilling a culture of data quality within the organization*."…Data quality is a culture, so if you don't have the right culture, so if we if we live purely in a culture where it's about, we must get the sales on the books and we must sell, OK, how does that then equate into their equality it doesn't."* 13:17 ¶ 4 in P4_GC

Other respondents proposed a solution saying that senior leadership should be held accountable for data quality. The respondent highlighted that leaders often prioritize matters that directly impact financial performance and suggests that linking data quality to the income statement or balance sheet could incentivize better data management by making it a financial concern. *"..if senior leadership is also held accountable on the quality of data and there's a direct link it's like at the moment if something doesn't impact my income statement as a senior level, should I worry about I won't…"* 2:70 ¶ 5 in P13_SN_2.

Furthermore, another respondent shared that their current organization proactively addresses this challenge by introducing a new data management tool. This strategic move is primarily motivated by the frustrations related to data quality issues. *"And I am addressing it, and we do escalate it to the different forums like I know even now is a bank they're trying to launch one data management tool, but it came from all this type of frustration with even how you do your data qualities. "* 2:56 ¶ 8 in P10_WB

Some highlighted the lack of readiness within their organization: "…*There's a drive towards being proactive and thinking about things like integration and all that, but it's almost like there's also an aspect of lack of readiness in how maybe it's because of how the systems and teams are structured, where there isn't any incentive to integrate and consolidate because that doesn't add to my key performance area."* 8:6 ¶ 10 in P12_TR

However, another respondent shed light on this challenge, attributing it to the perception of data as a valuable asset, especially prevalent in the banking sector. The respondent highlighted how some individuals within the organization assert their exclusive ownership of data, essentially claiming, "This is my domain." This dynamic root cause is attributed to annual restructuring, compelling individuals to safeguard their intellectual property, as access to data and information is a prized resource in a highly competitive landscape. *"…Because the challenge we have around the concept of sync data as an asset is more, protectionism is like we are protecting the data…Some position it so that this is my territory, right? …Every year, they restructure, and I think that puts people into a corner* *whereby they need to protect their IP because they are IP, whether it's access to that data, access to any information that's sort of their golden ticket to keep them in the game."* 7:20 ¶ 3 in P11_TM

5.6.1.1 Summary of RQ 3: Theme 1 – Data Sourcing and Data Integrity

In summary, the respondents offered a range of perspectives on integrating big data analytics into their organizational frameworks. While some expressed concerns about sourcing data and data quality during analysis, the majority cited issues related to legacy systems as a significant hindrance. These legacy systems, particularly in long-established banks, pose challenges in integrating data sources effectively.

Furthermore, the persistence of a silo mentality within banks was recognized as an impediment to the full potential of big data. The perceived lack of treating data as an asset and the absence of a culture of data quality within the organization were also critical concerns.

Several potential solutions were proposed, including holding senior leadership accountable for data quality to incentivize better data management. Some organizations want to introduce data management tools to address data quality issues. Some respondents pointed out a lack of readiness within their organizations, with the existing structures and teams not incentivized to integrate and consolidate data effectively.

Lastly, the perception of data as an asset, protectionism, and individual ownership of data within the organization was highlighted as a challenge driven by the competitive landscape and annual restructuring. Overall, these diverse perspectives shed light on the complex landscape of integrating big data analytics within various organizations and their multifaceted challenges.

5.6.2 RQ 3: Theme 2 – Fragmented architecture

The fragmented architecture theme poses a significant obstacle to the effectiveness of big data analytics integration into the organizational structure. This fragmentation leads to duplicated efforts and inconsistencies in data, hindering businesses' ability to collaborate and harness data for shared business objectives. Most respondents attributed the architecture fragmentation to the complexity of legacy systems within the business operating model.

"…but now that's some of the challenges, obviously need some of these particular legacy systems are so complex in, such a way that it's going to take years for, I would say our respective product was this two-point great into the emerging technologies." 3:28 ¶ 7 in P5_JX_3

Three of the respondents astutely pointed out that the practice of keeping data in separate silos presents a notable challenge, especially in the context of building a holistic customer profile. The respondent further elaborated on the obstacles faced by the bank when a customer applies for a specific financial product. To illustrate, they highlighted how the system for managing mortgages operates independently from the one for credit cards. Consequently, any updates made to a customer's information in one system may not be reflected in the other, resulting in a fragmented view of customer data. *"…A customer might come to the bank and apply for a vector product, and because we're very sorry, every system is separate from home loans and cards, for example, and they update the customer details that said, but the customer details they said remain."* 12:4 ¶ 3 in P3_DrTN

Another respondent added to this, mentioning that data is everywhere. *"…I would say in this organization is just purely access to data. Access to consolidate data, right? You have data, but it's all over the place. It's in a sequel server. It's in a warehouse. There's Hadoop there. It's on an Excel spreadsheet over there, so trying to get access to all of us valuable data to start their commercialization journey is another challenge."* 13:6 ¶ 3 in P4_GC

Another respondent highlighted that it would not be easy to integrate big data analytics into the current organizational structure as there appears to be a combination of systems operating simultaneously, some outdated, while others are more cutting-edge technologies. Consequently, compatibility issues arise, particularly regarding middleware, as different systems may interpret certain things differently. The participants explained that different teams use various systems for distinct purposes, creating a significant challenge in separate data storage areas. *"…So different systems for different things and therefore, I would say storage areas of data, and now the challenge with that is and achieving a single view of a customer, for example, becomes really, really a challenge because a customer might come to the bank and apply for a vector product and because our systems are separate from home loans and card for example, and they* *update the customer details that said, but the customer details they said remain.*" 12:76 ¶ 3 in P3_DrTN

Another respondent noted that despite the organization's efforts to establish a centralized data storage environment, the challenges persist for larger organizations due to the diverse array of data collection and storage platforms and different product teams. In certain instances, various teams may operate on different systems; for example, one team might rely on a certain system while the other relies on another. From the participants' perspective, this factor plays a pivotal role in the fragmentation of data architecture. *"…The other thing is also I think it is a challenge for the bigger organization because we've got a lot of platforms right where you collect and store data sometimes. So you might find teams with their data storage data, …"* 2:50 ¶ 7 in P12_TR.

However, some respondents pointed back to the lack of data leadership at the strategic level within the organization. *"…So I think for me if data can have a room even at the strategic level, like at the scene that influences be will easily be seen across cross organization because that will remove silos and that's one of the things"* 2:68 ¶ 7 in P13_SN_2. Some emphasized the importance of alignment between the data and business strategies, highlighting a prevalent issue where individuals operate in isolation, whether from an IT or data perspective. This isolation results in the development of disconnected strategies, leading to redundant data, inefficiencies, and challenges in achieving a cohesive organizational data view.*"…to get value out of data, we have to make sure that your data strategy talks to your business strategy … people are working in silo from an IT perspective or from a data perspective, you design your own strategy and maybe around infrastructures."* 2:67 ¶ 4 in P14_NH

5.6.2.1 Summary of RQ 3: Theme 2 – Fragmented architecture

The responses from the participants underscore the pervasive challenge of fragmented data architecture and its implications for the seamless integration of big data analytics within organizational structures. This fragmentation arises from the complexity of legacy systems within the business model and the widespread practice of segregating data into separate silos. The consequences of this fragmentation are substantial, encompassing duplicated efforts and inconsistencies in data that obstruct the organization's ability to collaborate effectively and leverage data for shared business objectives.

Compatibility issues also come to the fore when outdated and cutting-edge technologies coexist, particularly concerning middleware, leading to discrepancies in data interpretation. The challenge of accessing scattered data across various platforms further compounds the problem, impeding data commercialization efforts. While some respondents have attributed these challenges to the absence of data leadership at the strategic level, others have emphasized the critical need for alignment between data and business strategies to avoid working in isolated silos, which can result in disconnected strategies, redundant data, inefficiencies, and the inability to achieve a unified organizational data perspective.

5.6.3 RQ 3: Theme 3 - Single-View architecture

Most respondents expressed their frustration with the fragmented data landscape in the banking industry, highlighting the decentralized data challenge as a significant obstacle in data management projects that hinder the attainment of a unified data perspective. The respondent emphasized the need for a value-driven approach and effective governance, highlighting the absence of data leaders who can bridge the gap between business and IT, along with the lack of champions, which makes change management and implementation difficult, mentioning the common issue of initially identifying the wrong problem in data projects and end up just landing and landing data with no strategic use which ends up being costly to the organization.

"…Sometimes it's because the projects are starting off from an IT perspective, landing data and this landing landing landing data with no usage, not going from a value point of view, I cannot be driven from governance, and you know, especially banks into over government you know just learn everything with the same governance, same principle but nobody uses it. You spent so much money, and nobody used it because you didn't stock up with the user." 14:16 ¶ 3 in P7_NY_4

Most respondents highlighted difficulties in decentralized data management. They noted that the current configuration lacks collaborative efforts, with each business division operating independently. This isolation contributes to inconsistencies in business decision-making and makes it difficult to leverage data into the organization's strategies.

"…we need to remove those silos for us to be able to really get to the position of leveraging data in such a way that it can influence our strategies and remove multiple layers vertical layers and build one single layer of the truth." 7:18 ¶ 4 in P11_TM

In alignment with the sentiments expressed by other respondents regarding the hurdles of decentralized data management, another respondent echoed these concerns. They shared that they initially set out to establish a holistic customer view in their organization. However, given the multitude of touchpoints within the organization, creating a unified customer perspective has proven to be a substantial challenge. *"…And we've made headways, but we have not really gotten it right 100% right purely because, again, there are so many touch points in the organization, there are so many owners of the costume, one customer is owned by so many product houses, and they each define it differently."* 10:7 ¶ 86 in P1_AQ

One of the respondents gracefully alluded to the legacy systems, emphasizing that achieving a unified customer perspective is a voyage. Nevertheless, they expressed unwavering commitment within their organization to embark on this transformative journey. "…*So, you'll have the mortgage product costs of the vehicle finance or credit cards and with legacy systems and data and set up along those lines. And it's quite I think it's quite a difficult journey. It's a journey that everybody is paying attention to, but it is quite a difficult journey to bring all those different pieces together to really effectively make use of all the data that we have in decision-making processes."* 5:8 ¶ 2 in P9_LvO

5.6.3.1 Summary of RQ 3: Theme 3 - Single-View Architecture

The banking industry faces significant challenges due to a fragmented data landscape, primarily hindered by decentralized data management, as noted in Section 5.6.2. Respondents' express frustration at the lack of a unified data perspective, emphasizing the hurdles posed by decentralized data. They stress the need for a value-driven approach and effective governance to combat this issue. The absence of leaders bridging the gap between business and IT, alongside a lack of champions, complicates change management and implementation, leading to misdirected data projects and hefty financial costs for the organization.

The decentralized nature of data management is a recurring concern among respondents. They highlight a lack of collaboration between business divisions, resulting in inconsistencies in decision-making and an inability to utilize data in organizational strategies effectively. Achieving a unified customer perspective is challenging due to the numerous touchpoints within the organization, each defining customers differently.

The legacy systems further complicate the journey toward a unified customer view.

Despite acknowledging the difficulties, respondents express unwavering commitment to navigating this transformative journey within their respective organizations. They highlight the complexity of unifying diverse data sources but affirm a dedicated focus on leveraging data effectively in decision-making processes.

5.6.4 Conclusion of Research Question 3: Integrating Big Data Analytics for enhanced Decision-Making within existing organizational structures

The respondents noted that data is managed through two distinct capabilities: centralized and decentralized. Centralized data management focuses on establishing a unified data management model, while decentralized data management tailors data assets to the specific needs of individual divisions.

The primary challenge discussed by respondents was related to decentralized data management, which hindered achieving a single view of data. They emphasized the importance of a value-driven approach and effective governance. The absence of data leaders who can bridge the gap between business and IT and the lack of champions was identified as a barrier to effective change management and implementation. Furthermore, the common issue of initially misidentifying the problem in data projects and accumulating data without strategic use was highlighted, resulting in unnecessary costs for the organization.

Most respondents pointed out the difficulties associated with decentralized data management, citing a lack of collaboration among business divisions. This lack of coordination led to inconsistencies in decision-making and made it challenging to use data in the organization's strategies effectively. Additionally, the challenge of creating a unified customer perspective was discussed, with respondents noting the complexity of achieving this due to the multitude of touchpoints within the organization and the diverse ownership of customer data among different product houses.

Despite the complexities and challenges, there was a resounding commitment among respondents to undertake the journey towards a unified data perspective and effective data management within their organizations. The transformation was recognized as a difficult but essential process to harness the full potential of data in decision-making.

5.7 Perspective from the telecommunication industry

The participant from the telecommunication industry was asked the same questions, and overall, the discussion revolved around establishing a culture that values and optimizes data for business insights.

The findings indicated that the organization must achieve a data-driven culture to leverage big data analytics on data-driven decision-making. The participant stressed the importance of data quality, governance, and culture in leveraging data effectively and emphasizing the role of leaders and the need for investments, highlighting that a solid data foundation is crucial. The participant discussed the significance of architecture, data structure, and effective metadata management. The narrative outlines strategies for data stewardship, training, creating centers of excellence, and the necessity of merging technical and business perspectives. The participant also covered the challenges, such as resistance to change and financial constraints, suggesting that innovation and adaptability are vital.

The findings do align with the findings from the participants who are in the banking industry. However, the telecommunication big data analytics integration into data-driven decision-making within the organization is more mature when compared to the banking industry.

5.8 Conclusion

The impact of big data analytics on data-driven decision-making surfaces several pivotal considerations. Among these are aligning a data strategy with the overarching business strategy, recognizing the value of data, and fostering an ecosystem to extract valuable insights. A note of caution advises against accumulating excessive and unproductive data without clear alignment with business goals. Collaboration with business leaders, effective leadership, and appointing a Chief Analytics Officer emerge as recommendations to bridge the gap between data teams and the broader organization.

The need to demonstrate the incremental value of data and integrate it into business processes remains crucial to convincing stakeholders of its worth. Encouraging a longer-term focus is stressed to ensure sustained effectiveness in data-driven decision-making. Proactive data usage from customer transactions is identified as vital to addressing current needs and shaping future opportunities.

Leadership, Collaboration, and organizational culture notably influence the successful implementation of big data analytics in data-driven decision-making. The results reveal interconnected themes highlighting this impact. Leadership recognizes the scarcity of data skills and proactively takes measures to address it, including upskilling, promoting data literacy, and fostering value-driven competencies. Collaboration is a pivotal theme in data-driven decision-making, backed by supportive leadership structures encouraging forward-thinking approaches. Effective structuring of data analytics skills and fostering collaboration are highlighted, emphasizing the significance of business understanding, effective communication, and interpersonal skills.

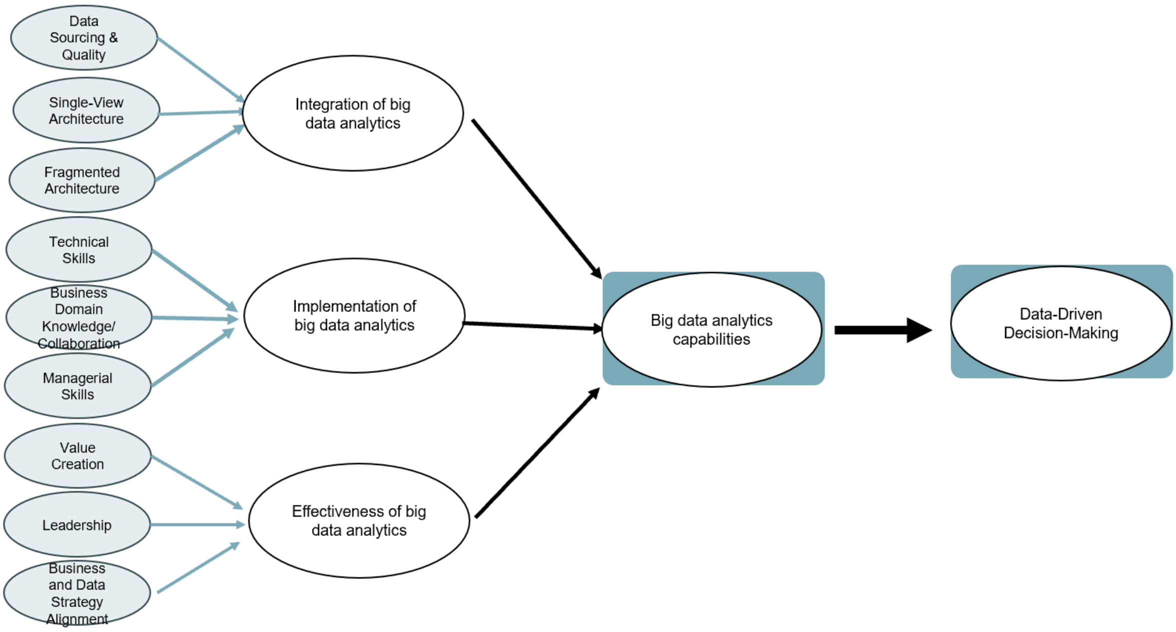
Encouraging community among data professionals and the wider business is pivotal for visibility, collaboration, and reducing reliance on personal relationships. However, siloed organizational structures hinder effective collaboration and data sharing.

Respondents pointed out that data is managed through two capabilities: centralized and decentralized data management. Decentralized data management challenges hinder achieving a unified data view. The absence of data leaders bridging the gap between business and IT and the issue of misidentifying problems in data projects are highlighted as barriers.

Difficulties associated with decentralized data management, the lack of collaboration among business divisions, and the challenge of creating a unified customer perspective were identified. Despite the complexities and challenges, a collective commitment among respondents to undertake the journey toward effective data management and a unified data perspective was palpable, recognizing it as an arduous yet essential process for leveraging the full potential of data in decision-making.

The below figure 10 illustrates the conceptual framework derived from the findings.

Figure 10: *Framework illustrating the findings.*



Source: Researcher's own

6 CHAPTER 6: ACADEMIC ARGUMENT

6.1 Introduction

In this chapter, an extensive analysis is undertaken to provide a comprehensive context for the findings unveiled in Chapter 5. The structure aligns with the research questions introduced in Chapter 3. Each research question and its associated theme(s) are examined and contrasted with the most recent academic discourse, as explored in the literature review in Chapter 2.

The primary objective of this comparative analysis is to enrich our comprehension of the utilization of big data analytics in data-driven decision-making processes within the landscape of South African banks. To achieve this, we have rigorously adhered to a systematic, consistent, and replicable approach in our comparative analysis, ensuring the thoroughness and internal validity of our findings.

6.2 Discussion of Research Question 1: The effectiveness of big data analytics on data-driven decision-making

How does big data analytics contribute to the effectiveness of data-driven decision-making?

According to the existing body of academic literature, it is widely acknowledged that big data analytics plays a crucial role in the curation and transformation of vast raw data into valuable insights and knowledge (Akhtar et al., 2019; Awan et al., 2021; Ghasemaghaei et al., 2018). This process is instrumental for businesses to adapt to changing dynamics and maintain a competitive edge in highly competitive markets (Dong & Yang, 2020; Grover et al., 2018). Elia et al. (2022) share this perspective and further emphasize that big data has emerged as a powerful catalyst to revolutionize decision-making processes effectively and has the potential to usher in new strategic approaches. Ghasemaghaei (2019) attests that proficiency in big data analytics substantially enhances decision-making quality and value creation (Dong & Yang, 2020; Grover et al., 2018).

Therefore, this research question aims to understand and explore the role and impact of big data analytics in improving the quality and outcomes of data-driven decision-making processes within the South African banking sector.

The findings from Section 5.4 revealed that several critical factors underscore the impact of big data analytics on data-driven decision-making. These include aligning data strategy with overall business strategy, effective leadership, and recognizing the value of data as an asset by establishing an ecosystem for extracting valuable insights. Caution is advised against accumulating excessive and unproductive data that lacks alignment with business objectives.

6.2.1 RQ1 – Theme 1: Business and Data Strategy Alignment

6.2.1.1 Evidence on Business and Data Strategy Should be Aligned from Literature

As per Suoniemi et al. (2020), a business strategy entails how a company generates value compared to its rivals by achieving cost leadership or differentiation and by considering the breadth of its target market (which could encompass the entire market or focus on specific market segments). In alignment with this notion, Grover et al. (2018) assert that the success of big data analytics and its achievement should be integrated into a company's enduring business strategy and the establishment of mechanisms for ensuring that the business is in harmony with this strategy. This alignment encompasses processes, regulations, protocols, the organizational framework and governance, and the corporate culture, all of which are vital for harnessing data to enhance competitiveness. Nevertheless, while Mikalef et al. (2021) perspective underscores the significance of prioritizing essential resources during the implementation of big data analytics, it falls short in addressing the inquiry about the deployment and integration of analytics within the broader strategic framework. Specifically, it fails to explore the potential obstacles in this process that could hinder the creation of value and making data-driven decision.

Despite companies' recent investments in big data analytics, an expanding body of scholars contends that adeptly applying big data analytics significantly contributes to enhancing organizational adaptability and overall performance (Hajli et al., 2020). Mikalef et al. (2021) underscore the importance of organizations proficiently disseminating and aligning their big data analytics initiatives with strategic objectives to realize specific, targeted performance outcomes. These initiatives are crucial in shifting traditional organizational decision-making towards data-driven decision-making (Li et al., 2022). Moreover, organizations that nurture a data-driven culture establish a robust linkage between their overall organizational strategy and a well-defined analytics strategy (Mikalef et al., 2019b).

However, Grover et al. (2018) attest to this and argue that incorporating big data analytics often has an IT-centric focus, but it is essential to have a big data analytics strategy that is primarily business-oriented. The key to big data analytics success lies in integrating big data analytics into the long-term business strategy of a company and establishing the necessary mechanisms to ensure alignment between big data analytics and the overall business strategy.

6.2.1.2 Evidence that Business and Data Strategy Should be Aligned from the Findings

In section 5.4.1, findings highlight the vital importance of aligning data and business strategies. Participants emphasized that data plays a pivotal role in shaping business strategy and underscored the significance of aligning data and business strategies to fully utilize data analytics for decision-making. They stressed the need for a clear data and analytics strategy that aligns seamlessly with the broader business strategy. Participants also recognized that the business strategy should guide the data strategy to prevent the accumulation of excessive, low-value data. Aligning strategies allows organizations to enhance sales, manage risks effectively, and evaluate overall business performance. Some organizations still rely on outdated business models, indicating opportunities for innovation through aligned big data analytics. However, achieving consistent alignment between business and data strategies remains challenging.

6.2.1.3 Comparative Analysis of Literature vs Findings

The findings emphasize the critical importance of aligning data and business strategies, with participants highlighting the pivotal role data plays in shaping business strategy. They underscore the need for a well-defined data and analytics strategy that seamlessly aligns with the broader business strategy, thereby preventing the accumulation of excessive, low-value data. This alignment is seen as essential for enhancing sales, effective risk management, and comprehensive evaluation of overall business performance. It is worth noting that some organizations still operate on outdated business models, suggesting potential innovation opportunities through aligned big data analytics. However, consistent alignment between business and data strategies remains a challenging endeavor.

Literature, as described by Suoniemi et al. (2020) and Grover et al. (2018), aligns with these findings, stressing that the success of big data analytics is contingent on its integration into the long-term business strategy. This alignment encompasses various aspects, including processes, regulations, protocols, organizational structure and governance, and corporate culture, which are critical for harnessing data to gain a competitive advantage. In this context, Mikalef et al. (2021) reinforce the importance of effectively disseminating and aligning big data analytics initiatives with strategic objectives to achieve specific, targeted performance outcomes, thus shifting traditional decision-making towards data-driven decision-making.

Nonetheless, the literature also acknowledges the challenge posed by an IT-centric focus in implementing big data analytics, as highlighted by Grover et al. (2018). They argue for a shift towards a business-oriented big data analytics strategy, highlighting the importance of aligning with the long-term business strategy and establishing mechanisms to guarantee this alignment. It is evident that while the literature reinforces the importance of aligning business and data strategies, it does not delve deeply into the potential obstacles and challenges that may impede this alignment, which the findings suggest is a common challenge in practice. This points to the need for further research to explore and address these challenges comprehensively, with a focus on the effective deployment and integration of big data analytics within the broader strategic framework.

6.2.1.4 Conclusion

The findings from the participants align with the literature in emphasizing the importance of aligning data strategy with business strategy, recognizing the value of data, and the strategic role of big data analytics. However, there are gaps in the literature regarding the obstacles to integrating analytics strategy with overall business strategy (Mikalef et al., 2021).

6.2.2 RQ1 – Theme 2: Effective Leadership

6.2.2.1 Evidence of Effective Data Leadership from Literature

A proficient method for guiding members within an organization begins with effective leadership (Grover et al., 2018; Shamim et al., 2019). Grover et al. (2018) further state that organizations with leadership teams possessing well-defined big data analytics strategies, clear objectives, and the ability to articulate the business rationale are more likely to achieve success. Attesting to this, Tabesh et al. (2019) further argue that the success of adopting new organizational initiatives hinges on the company's leadership's dedication to the developed strategies and their willingness to offer financial and structural backing throughout the implementation process. In order to boost organizational decision-making performance through the use of data analytics tools, managers must focus on improving the relevant competency dimensions (Grover et al., 2018). A leadership orientation toward big data can promote collaboration within and between organizations and facilitate knowledge exchange. Furthermore, leadership can cultivate the capabilities needed for effective big data decision-making by fostering a favorable climate (Awan et al., 2021; Shamim et al., 2019).

According to Mikalef et al. (2019b), companies that succeed in fostering a data-driven culture establish a robust alignment between their corporate strategy and a clearly defined analytics strategy. However, achieving this relies on top management's emphasis on elevating the significance of big data and analytics in decision-making. Effective endeavors often succeed when driven by a holistic, big data analytics strategy and capable leadership (Grover et al., 2018). In the contemporary landscape, managers increasingly rely on big data analytics for real-time decision-making and the guidance of future organizational initiatives (Mikalef et al., 2019b). In terms of human expertise, the literature acknowledges the necessity for a blend of technical and managerial skills to extract value from investments in big data. Grover et al. (2018) state that managers using data analytics for organizational decision-making should possess adequate domain knowledge to utilize the tools and accurately interpret the outcomes effectively. To enhance decision-making efficiency and effectiveness, organizations should maximize the utilization of big data analytics tools, facilitating the transition from traditional decision-making practices to data-driven decision-making (Li et al., 2022).

However, Mikalef et al. (2019b) and Shamim et al. (2019) contend that achieving success in big data initiatives is hindered by a significant challenge of unsupportive organizational culture and the presence of data silos that impede access to crucial data necessary for informed decision-making. To bridge this gap, Shamim et al. (2019) state that “attracting the right people with the right skills will be beneficial.” Moreover, to improve decision-maker proficiency, they should possess the skill to decipher the results of extensive data analysis and comprehend their significance (Grover et al., 2018).

6.2.2.2 Evidence of Data Leadership from Findings

Theme 1 centers on the crucial theme of aligning data strategy with broader business strategy. Most participants underscored the necessity of collaborative efforts between data teams and business leaders from various departments to address existing data challenges. This collaborative approach involves gaining a comprehensive understanding of the company's foremost challenges, emphasizing the role of data leaders who can bridge the gap between data teams and the wider organization. These leaders are expected to have a deep understanding of the intricacies of decision-making within big data analytics and be well-versed in the organizational elements required to facilitate data-driven decision-making processes.

Visibility and effective communication are recognized as pivotal in championing data initiatives and securing support from senior leaders. The appointment of a Chief Analytics Officer emerges as a top priority in the hope that this role will focus on aligning data analytics with the company's needs, particularly end-users. Furthermore, participants stress the importance of active engagement between the leader of the analytics community and business leaders from the outset of discussions and initiatives to ensure seamless integration of data-driven insights into overarching business goals, along with effective consolidation and delivery.

However, concerns were raised by two participants regarding organizations with data leaders lacking the necessary skills to comprehend the value of data. They emphasized the need for data leaders who can bridge the gap between technical and business aspects, serving as effective translators to ensure that data investments are optimally utilized. This highlights the critical role of leadership in leveraging big data effectively for strategic decision-making and the challenges associated with this role.

6.2.2.3 Comparative Analysis of Literature vs Findings

The literature consistently emphasizes effective leadership as a pivotal element in achieving success in big data initiatives. Well-defined big data analytics strategies, clear objectives, and the ability to articulate the business rationale are crucial for success. Leadership's commitment to the formulated strategies and the provision of financial and structural support throughout the implementation process are prerequisites for successfully adopting new organizational initiatives. Leadership's orientation toward big data is considered essential for promoting collaboration, knowledge exchange, and effective decision-making. The literature also underscores the need to combine technical and managerial skills to extract value from big data investments.

Both the findings and the literature acknowledge the challenges posed by an unsupportive organizational culture and the presence of data silos that hinder access to essential data for informed decision-making. To tackle this challenge, the literature suggests attracting individuals with the right skills and improving decision-makers proficiency in interpreting data analysis results.

6.2.2.4 Conclusion

In conclusion, the comparative analysis highlights the significant role of effective leadership in aligning data strategies with broader business objectives, fostering collaboration and knowledge exchange, and addressing challenges in implementing data-driven decision-making. This underscores the critical importance of leadership in the context of big data initiatives (Grover et al., 2018; Shamim et al., 2019; Tabesh et al., 2019; Awan et al., 2021; Mikalef et al., 2019b; Li et al., 2022).

6.2.3 RQ1 – Theme 3: Value creation

6.2.3.1 Evidence of Value Creation from Literature

The "Era of Data" is currently thriving, where an exceptional volume of data is being generated across various sectors and governmental bodies, giving rise to significant excitement as organizations are eager to harness the potential of big data analytics to generate value (Mikalef et al., 2019b). According to Chiheb et al. (2019) and Elia et al. (2020), value pertains to the business insights that can be derived from the application of big data analytics and be actionable (Nisar et al., 2021). These insights can be harnessed to generate value across various domains, including the enhancement of business processes, innovation in products and services, improvement in customer experiences and market positioning, optimization of organizational performance, and the establishment of intangible value like corporate image and reputation (Grover et al., 2018). In essence, value can be extracted from big data analytics when multidisciplinary team members collaborate to share, combine, and incorporate their varied expertise (Akhtar et al., 2019). As noted by Grover et al. (2018), when organizations recognize big data as a valuable resource, it becomes crucial for them to ascertain its genuine accounting, economic, financial, or strategic worth. Nevertheless, determining the monetary value of data poses a significant challenge for businesses (Grover et al., 2018).

A substantial effort has been made to deploy big data analytics solutions that integrate management, technology, and talent, as discussed by Elia et al. (2020). This effort aims to deliver value, gauge performance, and secure a competitive edge. However, opportunities for creating value from big data analytics can arise from various origins and yield diverse outcomes. As a result, organizations must establish a framework for generating value through which they can envision and execute big data initiatives. Promoting communication and collaboration between decision-makers and the big data analytics team throughout the various phases of the decision-making process enhances comprehension of business problems or opportunities. This is achieved by fostering a shared understanding of the decisions and their requirements (Chiheb et al., 2019). The abundance of technological solutions does not always lead to instant value creation, highlighting a gap between the potential and real-world value of big data analytics (Elia et al., 2020).

A study conducted by Hung et al. (2020) showed that in commercial banks, big data analytics is very useful in improving the banks' marketing and risk management performances. Although the impact of big data analytics is evident in performance, its overall importance sets apart high-performing and low-performing companies, granting organizations the capability to take a more proactive and agile approach to identifying new business opportunities (Mikalef et al., 2019b). Numerous organizations have employed big data analytics to gain insights into their operational performance, enhancing their overall organizational intelligence for informed decision-making. This has led to the development of agile organizational structures that can swiftly adapt to market and business environment shifts. Additionally, BDA has been instrumental in optimizing resource utilization and enhancing returns on assets (Grover et al., 2018).

While big data and analytics have garnered significant attention, the success rate of such projects and the strategic value they yield remain uncertain. The prevailing body of literature on big data analytics predominantly focuses on its potential for enhancing specific organizational functions, with relatively few studies delving into its broader impact on overall organizational value (Grover et al., 2018; Mikalef et al., 2019b). As a result, there is a limited understanding of the approach companies should take in managing their big data projects, and there is a lack of empirical evidence to support the claim that these investments result in measurable business outcomes (Mikalef et al., 2019b).

6.2.3.2 Evidence of Value Creation from Findings

The findings from Section 5.4.3 reveal that participants acknowledged the potential for creating value through the effective utilization of big data analytics, especially when it aligns with the broader business strategy. This signifies a notable departure from the conventional practice of primarily using data for reporting purposes, notably in domains like credit risk assessment and underwriting. Some participants underscored the importance of employing data to address specific business challenges rather than merely amassing data for its own sake. They stressed that business units should spearhead such initiatives. It was emphasized that progressively showcasing the value of data and integrating data science and modeling into core business operations were pivotal in convincing stakeholders of the data's worth. Participants expressed the belief that there remains untapped potential for gaining deeper insights into customers through data analysis. There were concerns that strategic endeavors often exhibit a short-term orientation and insufficient consideration of longer-term perspectives. While one participant had reservations about the predictive aspect of their approach, they believed it could be effective with the appropriate utilization. The opportunity to proactively harness data from customer transactions for driving business growth and fostering innovation was prominently highlighted.

6.2.3.3 Comparative Analysis of Literature vs. Findings

In extracting value from big data analytics, the study's results resonate with current literature, confirming the potential of impactful big data analytics when aligned with a holistic business strategy. This congruence underscores the pivotal role of aligning big data analytics with long-established business strategies, as the literature advocates. Moreover, both the study findings and the literature accentuate the significance of translating big data insights into actionable strategies for value generation. The study's participants highlight the value of incorporating data science and modeling into core business functions, reflecting an approach advocated in the literature by Mikalef et al. (2019b).

On the other hand, the challenges related to realizing value from big data analytics find common ground between the study's findings and the existing literature. The short-term focus of strategic endeavors and the intricacies associated with evaluating the financial worth of data pose considerable challenges, a perspective mirrored in Grover et al.'s (2018) work.

The importance of a multidisciplinary approach in big data analytics, wherein a diverse array of skills contributes to value extraction, receives unanimous support from the study's findings and the literature, as expressed by Chiheb et al. (2019) and Akhtar et al. (2019).

The potential for value creation in various domains through big data analytics, such as process enhancement, product innovation, customer experience optimization, and organizational performance improvement, is a shared recognition between the findings and Grover et al.'s (2018) insights.

However, the literature underlines the uncertainty and challenges related to big data analytics initiatives' success and value creation. While the study participants suggest that the actual success rate and the strategic value from these endeavors remain uncertain, the literature emphasizes the limited focus on the broader impact of big data analytics on overall organizational value, as highlighted by Mikalef et al. (2019b) and Grover et al. (2018).

6.2.3.4 Conclusion

The findings complement the existing literature, emphasizing the significance of strategic alignment, actionable insights, a multidisciplinary approach, and value creation potential in various domains through big data analytics. However, they also concur on the uncertainties and challenges in achieving success and value from these initiatives.

6.3 Discussion of Research Question 2: Effective implementation of big data analytics on data-driven decision-making

Findings for Research Question 2 reveal that organizational culture and leadership play a significant role in successfully implementing big data analytics for data-driven decision-making in the South African banking industry. Leadership recognizes the shortage of data skills and takes proactive steps to address this by upskilling employees, promoting data literacy, and encouraging value-driven skills. They invest in data-related initiatives, assess their impact, and foster a cultural shift towards valuing data as a strategic asset. Collaboration is identified as crucial, with effective structuring of data analytics skills and a focus on skills like business understanding, communication, and interpersonal abilities.

Building a sense of community among data professionals and the broader business is emphasized to enhance visibility, promote collaboration, and reduce reliance on personal relationships for effective collaboration. However, challenges related to siloed organizational structures must be addressed to prioritize collaboration and data sharing for successful data-driven decision-making.

To unlock the potential advantages of big data, organizations need a blend of both tangible and intangible resources, encompassing human resources, cultural factors, technology, and managerial as well as technical skills (Shamim et al., 2019). Utilizing big data to enhance decision-making introduces significant management challenges, such as attracting individuals with the right skill set (Mikalef et al., 2018). However, it is important to note that these factors, while essential in facilitating the process, do not represent the ultimate desired outcome. The ultimate objective of this endeavor is to achieve high-quality data-driven decision-making (Akhtar et al., 2019; Shamim et al., 2019), which, according to literature, derives value from big data investments (Mikalef et al., 2019b).

6.3.1 RQ2 – Theme 1: Essential Skill Sets for Effective Implementation of Big Data Analytics

6.3.1.1 Evidence of Essential Skill Sets for Effective Implementation of Big Data Analytics from Literature

To produce valuable knowledge and insights guiding decision-making, companies must possess high-quality data, suitable information systems, analytical tools, and proficient human analytics talent (Chen et al., 2022; Dubey et al., 2021). Their ability to employ big data analytics and formulate strategic decisions based on data insights is highly dependent on the skills and knowledge of human resources (Mikalef et al., 2018). According to Chen et al. (2022), Dubey et al. (2021), and Mikalef et al. (2018), these skills can be further divided into technical knowledge, business knowledge, relational knowledge, such as communication and collaboration skills among employees from diverse backgrounds, and business analytics knowledge, encompassing data skills. Furthermore, as posited by Mikalef et al. (2018), combining these big data analytics skills introduces the concept of Big Data Analytics Capabilities (BDAC). This capability is broadly defined as a company's capacity to utilize data management, infrastructure, and talent (Mikalef et al., 2018; Mikalef et al., 2019b).

Mikalef et al. (2018) and Shamim et al. (2019) further underscore the pivotal role played by the data scientist within the big data domain. He further emphasizes that, in practice, the data scientist can effectively comprehend and address business challenges. Shamim et al. (2019) further state that the growing significance of these experts in big data underscores the utmost importance for organizations to retain them. At the same time, analytical thinking about data is a fundamental component of data science (Akhtar et al., 2019). Ghasemaghaei (2019) argues that analytical thinking skills should be an essential component for the entire organization as analytics provides knowledge sharing by enabling firms to distribute knowledge obtained through data analysis. He further states that firms that extensively use data analytics are better positioned to share knowledge and, in turn, enhance their decision quality. Shamim et al. (2019) highlighted the pivotal role to be played by data professionals and possess the ability to communicate effectively in the language of business, thus aiding leaders in addressing shortages in big data analytics skills and business skills. The shortage of adequately skilled employees, a common issue observed in various studies, presents a substantial obstacle to fully realizing the potential of big data analytics (Elia et al., 2020; Grover et al., 2018; Mikalef et al., 2018).

However, the success of big data analytics relies on comprehending the factors that impact its effectiveness on a company's performance (Akhtar et al., 2019). Ultimately, it is crucial to possess a comprehensive grasp of the firm's objectives and skills to measure and enhance vital key performance indicators. This is particularly significant because big data analytics initiatives are typically centered around addressing existing issues. Hence, the capability to identify these challenges and enhance them using insights derived from big data is a crucial element of the knowledge that business executives and data analysts should possess (Elia et al., 2022; Mikalef et al., 2019b; Yasmin et al., 2020). Knowledge sharing is a practice that can enhance access to information required for decision-making and consequently improve decision quality (Ghasemaghaei et al., 2018; Ghasemaghaei, 2019).

Ghasemaghaei et al. (2018) agree that individuals utilizing data analytics should not lack the necessary analytical skills and domain expertise; otherwise, that could hinder the enhancement of decision-making performance within organizations. They also mention that the ample availability of data has minimal inherent value unless skillfully utilized to improve organizational performance. This necessary domain knowledge involves a profound comprehension of the procedures, facts, and processes specific to a particular firm or industry. Armed with sufficient domain knowledge, analysts are more adept at recognizing crucial attributes and tackling the business challenges relevant to the organization (Ghasemaghaei et al., 2018).

6.3.1.2 Evidence of Essential Skill Sets for Effective Implementation of Big Data Analytics from Findings

The findings from Research Question 1: Theme 3 underscore the banking industry's imperative to shift towards problem-solving with data rather than mere data accumulation to create value from the data and foster data-driven decision-making. Participants stressed the need for business-driven leadership in such initiatives, incremental value demonstration, integration of data science into business processes, and the untapped potential for deeper customer understanding through data analysis. However, to do that, the business needs the capability to translate this value creation from big data analytics to understandable business language.

The findings for Research Question 2 have, therefore, stressed these capabilities. There is an acknowledgment that banks have accumulated the necessary resources to establish a unified and well-managed data source that supports diverse purposes and informed decision-making. However, the findings emphasized the importance of equipping employees with proficiency in data and business skills to effectively drive the implementation of big data analytics into data-driven decision-making. Bridging the gap in language and understanding between data specialists and business professionals is deemed crucial. Additionally, the need to instill a value-driven mindset in data scientists and analysts, enabling them to think from a business perspective, has been highlighted. Some recognize that banks are still fully realizing the potential of data, facing competition for data skills in the market, and addressing strategies for retaining these resources.

In response to these challenges, the results highlight the importance of enhancing the skills of in-house staff and promoting self-sufficiency among the workforce. They also highlight the shortage of data science and analytical skills and propose creating educational pipelines from universities to address this gap. In contrast, others emphasize business skills as the most critical, highlighting the need for individuals with strong data skills who also understand the intricacies of the business. Improving business and data literacy was stressed to bridge the knowledge gap and promote alignment within the organization.

6.3.1.3 Comparative Analysis of Findings vs Literature

Both the findings and the literature highlight the crucial role of essential skill sets in effectively implementing big data analytics. The findings emphasize the need to shift towards problem-solving with data rather than mere accumulation, driven by business leadership, value demonstration, and data integration into business processes. This corresponds with the literature, which emphasizes the significance of producing valuable insights for decision-making through high-quality data, suitable information systems, analytical tools, and proficient human analytics talent (Chen et al., 2022; Dubey et al., 2021).

The findings recognize the shortage of data skills and propose upskilling employees and bridging the language gap between data specialists and business professionals. In the literature, this is mirrored by the emphasis on technical, business, relational, and business analytics knowledge as essential skills for utilizing big data effectively (Mikalef et al., 2018).

The findings highlight the importance of cultivating a data-driven culture, a concept supported in the literature through big data analytics and capabilities, and the organization's ability to leverage data management, infrastructure, and talent (Mikalef et al., 2018; Mikalef et al., 2019b). The pivotal role of data scientists in comprehending and addressing business challenges is emphasized in both the findings and the literature, highlighting the need for organizations to retain such experts (Shamim et al., 2019).

However, both the findings and literature recognize the challenge of a shortage of adequately skilled personnel as a major obstacle to fully harnessing the potential of big data analytics (Elia et al., 2020; Mikalef et al., 2018). To confront this obstacle, the findings propose internal upskilling and educational pipelines from universities, while the literature suggests that enhancing business and data literacy is crucial (Akhtar et al., 2019).

6.3.1.4 Conclusion on Essential Skill Sets for Effective Implementation of Big Data Analytics

The findings and literature converge on the importance of essential skill sets encompassing technical, business, relational, and data skills and the need to retain data professionals. The shortage of adequately skilled personnel emerges as a common challenge that must be overcome to realize the potential of big data analytics fully.

6.3.2 RQ2 – Theme 2: Data-Driven Culture

6.3.2.1 Evidence of Data-Driven Culture from Literature

In the age of big data, numerous organizations aim to secure a competitive advantage by adopting the strategy of becoming data-driven (Grover et al., 2018; Yasmin et al., 2020). Quality data has become a cornerstone for various organizations, significantly improving decision-making and adaptability in dynamic environments (Awan et al., 2021; Yasmin et al., 2020). Shamim et al. (2019) attest to this and further state that data-driven organizations seek to foster a culture where reliance on data replaces reliance on intuition and hunches. Grover et al. (2018) attest to the importance of a "data-driven mindset" as a key indicator of big data value to companies, highlighting the significance of fact-based decision-making cultures. It is worth noting that some organizations merely pretend to be data-driven, making traditional decisions and then bolstering them with data, which can undermine the essence of big data decision-making (Shamim et al., 2019, 2020b).

According to (Lu et al., 2020), a culture centered around data-driven practices prioritizes testing and experimentation, giving greater importance to data over opinions. It also embraces the idea that failure is acceptable if it leads to valuable insights. Organizations that adopt a data-driven mindset have the potential to enhance their operations and surpass their competitors. Lu et al. (2020) further state that these organizations are increasingly turning to advanced analytics, including predictive and prescriptive analytics, to uncover and leverage fresh business insights, which are then used for decision-making (Awan et al., 2021). The transition to advanced analytics often demands expertise not commonly found within the organization. To bridge this gap, as proposed in RQ 2: Them 1 - Essential Skill Sets for Effective Implementation of Big Data Analytics, investing in upskilling employees and fostering better communication between data specialists and business professionals is essential. This resonates with Mikalef et al. (2018) on the emphasis on vital competencies for successfully utilizing big data, including technical proficiency, business acumen, relationship-building skills, and a solid grasp of business analytics.

This shift requires the right expertise and technological infrastructure and a supportive organizational culture and governance to realize its full potential (Yasmin et al., 2020).

This transition enhances decision-making capabilities, organizational adaptability, resource utilization, and financial performance (Grover et al., 2018; Yasmin et al., 2020). As Hung et al. (2020) indicated, the need for robust decision support for business administrators and data domain experts is paramount.

However, Mikalef et al. (2018) further argue that becoming a data-driven organization is a multifaceted endeavor, requiring attention from managers at multiple levels. Scholars have introduced the concept of "big data analytics capability" to represent a company's proficiency in leveraging big data for strategic and operational insights (Mikalef et al., 2018). Leadership's role in promoting a data-driven culture is paramount for aligning strategy with the organizational infrastructure (Grover et al., 2018).

Reports from professionals emphasize the significance of instilling a data-driven culture within organizations. Without such a culture, attempts to develop organization-wide capabilities through big data analytics may prove unsuccessful (Mikalef et al., 2019b). In evolving business environments, firms recognize the importance of becoming more data-oriented and the crucial role of big data in decision-making (Shamim et al., 2019).

For the successful implementation of big data analytics into data-driven decision-making, a strong data-driven culture and effective data governance structures are essential (Grover et al., 2018; Mikalef et al., 2019b). A culture that embraces data-driven principles strongly emphasizes a decision-making process (Shamim et al., 2019; Yasmin et al., 2020). In this culture, data takes precedence over opinions, and even failure is tolerated, provided that it results in valuable learning experiences (Lu et al., 2020; Shamim et al., 2019). Organizations that adopt a data-driven approach open doors to enhance their business operations and potentially surpass other entities (Awan et al., 2021; Shamim et al., 2019; Yasmin et al., 2020). The value derived from big data analytics is contingent on addressing weak links in the value-creation process, such as data quality and resource commitment (Grover et al., 2018). To achieve favorable results in big data projects, it is crucial to dismantle organizational silos and integrate expertise and knowledge from various departments (Mikalef et al., 2019b).

6.3.2.2 Evidence of Data-Driven Culture from Findings

The findings from Section 5.5.2 (RQ2: Theme 2 – Data-Driven Culture) reveal a notable shift towards a more data-oriented culture within organizations, particularly in the South African banking sector. Participants observed a change in leadership's enthusiasm for data, understanding its importance, and a willingness to invest in data-related initiatives. This shift has resulted in a growing focus on data and the introduction of key initiatives to integrate data into daily banking operations, ultimately leading to an improved data culture compared to a decade ago.

However, while there is evidence of progress in generating data use cases and promoting data literacy, participants still highlighted challenges. One key challenge is the shortage of data skills, especially in non-financial risk areas. Organizations have responded by initiating programs tailored to their specific needs, aiming to equip employees with the necessary data-related skills and enhance data literacy throughout the organization.

Accountability for data quality was another important concern. Participants emphasized the need to quantify data's impact on financial statements, such as the income statement or balance sheet, to ensure senior leadership takes data management seriously. This measurement could also align data strategy with overall business goals and promote the recognition of data as a valuable asset.

Participants also pointed out the lack of data domain expertise as a significant obstacle. They stressed the importance of individuals who possess deep, domain-specific knowledge of data, not limited to data professionals but to those with a comprehensive understanding of data within a specific domain.

Another cultural challenge identified was the existence of silos within organizations, where individuals are territorial and control their specific areas. This territorial behavior sometimes hinders the development of a data-driven culture. Concerns related to data confidentiality were also raised, but participants suggested alternative strategies like data masking to address these concerns.

To foster a data-driven culture, participants called for the implementation of programs to elevate the visibility of data and position it as a valuable asset within the organization. However, some participants noted that certain business units were still resistant to embracing data-driven decision-making, preferring to rely on past experiences or solutions without considering their suitability for the organization.

6.3.2.3 Comparative Analysis of Findings vs Literature

The study's findings reveal a significant shift toward a more data-oriented culture within organizations, especially in the South African banking sector. This shift is characterized by growing enthusiasm among leadership for data, an understanding of its importance, and increased investments in data-related initiatives, resulting in an enhanced data culture compared to a decade ago.

However, despite the progress, several challenges persist. One significant challenge is the shortage of data skills, particularly in areas like non-financial risk. Organizations have initiated tailored programs to address this gap to equip employees with the necessary data-related skills and enhance data literacy throughout the organization. This aligns with the literature emphasizing the importance of technical expertise and business analytics knowledge as essential skills for utilizing big data effectively (Mikalef et al., 2018).

Accountability for data quality is another concern, with participants emphasizing the need to measure data's impact on financial statements. This measurement ensures senior leadership takes data management seriously and aligns data strategy with broader business goals. This resonates with the literature's focus on the significance of data-driven mindsets and fact-based decision-making cultures (Grover et al., 2018).

Participants also highlighted the lack of data domain expertise as a significant obstacle, emphasizing the importance of individuals with deep knowledge of specific data domains. They stressed that this expertise should extend beyond data professionals to anyone with a comprehensive understanding of data within their domain. This echoes the literature's emphasis on the role of data domain expertise in data-driven decision-making (Grover et al., 2018; Yasmin et al., 2020).

Cultural challenges, such as the existence of silos within organizations and concerns related to data confidentiality, were also noted. Participants suggested strategies like data masking to address these concerns and promote a data-driven culture. This aligns with the literature's emphasis on the need for cultural changes and governance structures to support data-driven decision-making (Grover et al., 2018).

The literature highlights the significance of becoming data-driven in the era of big data to maintain a competitive edge (Grover et al., 2018; Yasmin et al., 2020). It emphasizes the importance of a culture that prioritizes testing, experimentation, and data over opinions and accepts failure if it leads to valuable insights (Lu et al., 2020; Shamim et al., 2019). The literature also highlights the crucial role of leadership in cultivating a culture centered around data-driven practices and emphasizes the necessity to develop a robust mindset geared towards data-driven approaches (Grover et al., 2018; Shamim et al., 2019).

Furthermore, it emphasizes the importance of advanced analytics, such as predictive and prescriptive analytics, in uncovering fresh business insights for decision-making (Awan et al., 2021; Shamim et al., 2019). This transition often requires expertise not readily available within the organization, underscoring the need for upskilling employees and improving communication between data specialists and business professionals. This aligns with the literature's emphasis on essential skills and competencies in big data analytics for effective implementation (Mikalef et al., 2018).

Overall, the findings and literature highlight the growing importance of data-driven cultures in organizations and the challenges and opportunities associated with this shift. It is about the right technological infrastructure and supportive organizational culture and governance to fully realize the potential of data-driven decision-making. This transition enhances decision-making capabilities, organizational adaptability, resource utilization, and financial performance (Grover et al., 2018; Yasmin et al., 2020). It also emphasizes the need for essential skills and competencies in big data analytics for effective implementation (Mikalef et al., 2018).

6.3.2.4 Conclusion

The findings and literature highlight the growing importance of data-driven cultures in organizations and the challenges and opportunities associated with this shift. It is about the right technological infrastructure and supportive organizational culture and governance to fully realize the potential of data-driven decision-making. This transition enhances decision-making capabilities, organizational adaptability, resource utilization, and financial performance (Grover et al., 2018; Yasmin et al., 2020). It also emphasizes the need for essential skills and competencies in big data analytics for effective implementation (Mikalef et al., 2018).

6.3.3 RQ2 – Theme 3: Collaboration

6.3.3.1 Evidence of Collaboration from Literature

Big data analytics is recognized as a significant catalyst for creating business value by making informed data-driven decisions (Akhtar et al., 2019; Awan et al., 2021) and improving competition (Mikalef et al., 2020). Nevertheless, organizations encounter challenges in harnessing the potential of BDA, as several surveys reveal that most big data analytics projects fall short of delivering tangible business benefits (Hagen & Hess, 2021).

To effectively harness the capabilities of big data analytics, organizations need tangible assets, such as technology; intangible assets, like a data-driven culture; and human resources (findings for Theme1 RQ2). Human resources encompasses technical expertise, involving the proficiency to utilize new technologies for extracting valuable insights from big data and managerial skills, which entail the knowledge of when and where to apply big data analytics insights in a business context (Hagen & Hess, 2021).

Human competencies and expertise are relevant, as integrating data science proficiencies and managerial capabilities can effectively address the mentioned challenges. This viewpoint aligns with research on IT capabilities, which underscores that technical and organizational skills are pivotal dimensions of human resources (Hagen & Hess, 2021). Furthermore, it is essential to establish a productive and collaborative connection between data science specialists (such as data scientists and data engineers) and other functional managers (for instance, those in the marketing or supply chain department) (Mikalef et al., 2018). An effective partnership between these two factions is vital for the triumph of big data analytics projects, as the application of data insights in business operations has been recognized as the most significant factor in realizing the business value of big data analytics. In light of the disappointing contributions observed in many big data analytics projects, enhancing collaboration between data experts and functional managers is imperative (Côrte-Real et al., 2019).

A data scientist must possess a comprehensive skill set encompassing robust analytical capabilities and profound business acumen (Hagen & Hess, 2021). The term 'collaboration' originates from the Latin words 'com' (together) and 'laborare' (to work), signifying the joint effort of two or more individuals on an intellectual task. Collaboration in groups aims to generate value that cannot be achieved by individual efforts, capitalizing on various skills and diverse backgrounds (Hagen & Hess, 2021).

According to (Hagen & Hess, 2021), collaboration for big data analytics involves three key aspects. First, data experts must cooperate within their own domain to develop exceptional data science solutions. Second, business managers should collaborate within their respective spheres to harness cross-functional data insights, such as obtaining a comprehensive view of customers across all interactions. Third, the collaboration between the data and business communities is crucial, as they must combine their technical and managerial expertise to generate business value through BDA. This study primarily focuses on this third form of collaboration (Hagen & Hess, 2021).

6.3.3.2 Evidence of Collaboration for Big Data Analytics from Findings

Collaboration emerged as a significant and recurring theme in the discussions regarding adopting data-driven decision-making within the organization. This finding highlights the importance of cultivating a collaborative culture that allows leadership to consider how to establish an effective leadership structure supporting more expansive and forward-thinking approaches, particularly in optimizing data analytics skills. Participants stressed the significance of various skills, particularly business understanding, effective communication, and interpersonal abilities. They emphasized the need for individuals with data skills to excel in business understanding, communication, and collaboration to identify and capitalize on valuable opportunities successfully.

Furthermore, participants underscored the importance of analytics professionals immersing themselves in the business to understand the organization's inner workings profoundly. This hands-on experience enables them to deliver analytics solutions finely tuned to the business context. Alignment with business needs was highlighted as a top priority, with regular conversations with business leaders essential to ensure that every project meets these needs effectively. Creating a sense of community among data scientists, analysts, and the business was emphasized as a vital element to foster visibility, encourage conversations on leveraging insights, and eliminate the need for personal relationships as a prerequisite for collaboration.

However, collaboration was also acknowledged as a prevalent challenge, particularly in organizations with a silo mentality, where different business units compete against each other. Organizations should adopt a more comprehensive perspective to enhance collaboration, focusing on their overarching objectives and how best to serve customers beyond a product-centric approach.

6.3.3.3 Comparative Analysis of Findings vs Literature

The findings from this study underscore the significance of cultivating a collaborative culture within organizations, aligning with the literature that recognizes the importance of collaboration in achieving business value through big data analytics (Akhtar et al., 2019; Awan et al., 2021). The findings stress the importance of various skills, particularly business understanding, effective communication, and interpersonal abilities, in line with prior research emphasizing the need for a combination of technical and managerial skills (Hagen & Hess, 2021). The findings highlight the need for analytics professionals to immerse themselves in the business, reflecting the literature's emphasis on integrating data science proficiencies and managerial capabilities to address challenges effectively (Hagen & Hess, 2021). The findings also acknowledge the prevalent challenge of collaboration in organizations with a silo mentality, echoing the literature's recognition of the need for collaborative relationships between data science specialists and functional managers for project success (Mikalef et al., 2018; Côrte-Real et al., 2019). The multifaceted skill set of a data scientist, combining analytical capabilities and business acumen, is considered essential for big data analytics success, aligning with the literature's perspective (Hagen & Hess, 2021).

The literature highlights the role of big data analytics in making informed data-driven decisions and improving competitiveness (Akhtar et al., 2019; Awan et al., 2021). However, it also acknowledges the challenges organizations face in harnessing the potential of big data analytics projects (Hagen & Hess, 2021). The need for tangible assets, intangible assets, and human resources is recognized in alignment with the study's findings on the importance of collaboration, skills, and immersion in the business context (Hagen & Hess, 2021). The literature emphasizes integrating technical and managerial skills in addressing challenges, reflecting the study's focus on combining data science proficiencies and managerial capabilities (Hagen & Hess, 2021). Additionally, the importance of collaboration between data science specialists and functional managers is highlighted as essential for the success of big data analytics projects, mirroring the study's emphasis on fostering collaboration within the organization (Mikalef et al., 2018; Côrte-Real et al., 2019). The study and literature collectively stress the multifaceted skill set of a data scientist, emphasizing its critical role in the effective utilization of big data analytics (Hagen & Hess, 2021).

6.3.3.4 Conclusion

The findings and the literature recognize that collaboration is essential in the context of big data analytics, with a particular focus on the need for collaboration between data experts and functional managers. The findings further offer practical insights into how organizations address collaboration challenges and opportunities in the context of data-driven decision-making.

6.4 Discussion of Research Question 3: Integrating Big Data Analytics for enhanced Decision-Making within existing organizational structures

It is imperative to develop a data management framework capable of accommodating diverse big data analyses and providing real-time business insights to users on demand, allowing them to access the information they require when it is needed swiftly (Grover et al., 2018). According to Grover et al. (2018), effectively implementing big data analytics involves facing substantial hurdles in integrating diverse and disparate data from data sources, encompassing pre-existing data such as that stored in legacy systems and new data, both structured and unstructured, which is essential for extracting value from big data analytics.

As discussed in Section 6.3, many of the challenges associated with leveraging big data analytics in data-driven decision-making are rooted in organizational culture rather than issues related to data or technology (Awan et al., 2021). In the evolving landscape of big data, characterized by the five V’s (Volume, Velocity, Variety, Veracity, and Value), big data analytics diverge from conventional investments in structured, unchanging, and purposefully collected data. These infrastructure investments can yield tangible business value (Grover et al., 2018; Mikalef et al., 2019b) and enhance quality data-driven decision-making (Shamim et al., 2019).

6.4.1 RQ3 – Theme 1: Data Sourcing and Integrity

6.4.1.1 Evidence of Data Sourcing and Integrity from Literature

In addition to the fundamental 3 V’s (Volume, Velocity, and Variety) of big data (Elia et al., 2020; Mikalef et al., 2020), the concept encompasses an additional aspect known as "Value," as discussed in RQ1: Theme 3 – Value Creation. Furthermore, an attribute of

"Veracity," as identified by Ghasemaghaei et al. (2018) and Wang et al. (2019), adds another dimension to big data by underlining the importance of data quality and the level of trust associated with diverse data sources. Scholars have expanded upon the characteristics of big data, introducing the concept of "Variability" as another dimension, accounting for the inconsistencies in data flow (Ghasemaghaei et al., 2018). However, given the high velocity, high variety, and high volume of data increase, the risk of data inaccuracy is unescapable (Ghasemaghaei et al., 2018; Mikalef et al., 2019b).

Despite the widely recognized importance of data quality as an essential prerequisite for decision-making (Chen et al., 2022; Dubey et al., 2021; Ghasemaghaei et al., 2018), indications show that organizations typically rely solely on internal data sources (Jha et al., 2020). Moreover, data generated within the organization originates from outdated legacy systems incapable of adapting to the organization's evolving needs. However, analyzing extensive datasets and deriving insights from them can assist the organization in making well-informed decisions and gaining a competitive edge (Jha et al., 2020). These legacy systems cannot be easily replaced, although they need to be integrated into big data analytics. According to Jha et al. (2020), " Legacy Data has rigid format issues that do not suit Big Data Applications" (p11). Grover et al. (2018) attest to this by stating that organizations must possess robust competencies for integrating, administering, disseminating, and examining large volumes of data in various formats to facilitate different value-generating requirements. This integration should uphold data precision and consistency and be addressed through the organization's chosen Big Data framework and architecture (Grover et al., 2018; Mikalef et al., 2021).

6.4.1.2 Evidence of Data Sourcing and Integrity from Findings

The findings provide a diverse range of perspectives from the respondents. Most identified the prevailing dynamics as substantial barriers to data integration within the South African banking sector.

Respondents highlighted data sourcing challenges and data quality during analysis, while the hindrance posed by legacy systems in data source integration was a major concern, particularly in long-established institutions. Other respondents voiced doubts about the industry's treatment of data as a valuable asset and emphasized the significance of instilling a data quality culture within the organization. The findings suggested that senior leadership should be held accountable for data quality, and linking data quality to financial performance could incentivize better management. To address this concern, one organization has taken the initiative to introduce a data management tool to enhance the overall quality of the organization's data. However, the perceived data as an asset, protectionism, and individual ownership of data within the organization were highlighted as a challenge driven by the competitive landscape and annual restructuring.

6.4.1.3 Comparative Analysis of Findings vs. Literature

The findings echo the importance of data quality, which aligns with the literature. Ghasemaghaei et al. (2018) and Wang et al. (2019) stressed the significance of data quality and trust associated with diverse data sources, introducing the concept of "Veracity." Respondents in the study also highlighted data quality as a concern. This consistent focus on data quality indicates its critical role in data integration.

As mentioned in the findings, the challenge posed by legacy systems in data source integration is corroborated by Jha et al. (2020), who argued that legacy systems are inflexible and unsuitable for big data applications. Grover et al. (2018) further emphasize the need for robust competencies to integrate, administer, and examine large volumes of data in various formats. This suggests legacy systems remain a substantial obstacle to data integration within the South African banking sector.

The study findings highlight concerns regarding the industry's treatment of data as a valuable asset and protectionism and individual ownership of data within organizations. This aligns with the competitive landscape and annual restructuring within the sector. The literature supports the idea that data is an asset that can provide a competitive advantage (Elia et al., 2020; Mikalef et al., 2020). However, the study's findings suggest that these concepts are not fully embraced within the South African banking sector, which may hinder effective data integration.

The findings indicate a need to hold senior leadership accountable for data quality and link it to financial performance as an incentive for better data management. While this aspect is not directly addressed in the reviewed literature, it aligns with the broader idea that data governance and quality should be integral parts of organizational culture to achieve data integration goals.

6.4.1.4 Conclusion

The findings and existing literature reveal several common challenges and concepts in the South African banking sector's journey toward effective data integration. Data quality, legacy systems, the treatment of data as an asset, and accountability for data management are shared concerns that need to be addressed for successful data integration. The literature provides a foundation for understanding these challenges, and the study's findings shed light on their relevance in the specific context of the South African banking sector. Addressing these challenges is crucial for the sector to harness the full potential of data for informed decision-making.

6.4.2 RQ3 – Theme 2: Fragmented Architecture

6.4.2.1 Evidence of Fragmented Architecture from Literature

Data have become the most invaluable and treasured resource within the banking industry today Chen et al., 2022; Dubey et al., 2021; Ghasemaghaei et al., 2018). Nonetheless, they pose a persistent challenge for businesses due to their constant expansion in diversity, intricacy, and dispersal (Ghasemaghaei et al., 2018). In reality, a significant portion of the data that banking institutions accumulate and maintain is stored in various isolated or fragmented repositories (Soldatos & Kyriazis, 2022). According to Mikalef et al. (2019b), and Soldatos and Kyriazis (2022), this has been highlighted as a major obstacle encountered by managers when seeking to establish big data initiatives; the lack of support from the organizational culture and the presence of data silos that restrict access to essential data required for gaining valuable insights. Fostering a data-driven culture within an organization, which combines data insights and managerial judgment effectively, relies on the support of top management and a thorough appreciation of the opportunities unlocked by big data analytics (Mikalef et al., 2019). However, to become a data-driven organization, it is essential to incorporate big data analytics into the organizational strategy (Awan et al., 2021; Mikalef et al., 2021), institute governance structures, and enact processes that enable the unrestricted movement of data throughout the organization, thereby dismantling departmental silos (Mikalef et al., 2019b; Soldatos & Kyriazis, 2022).

To attain favorable outcomes in substantial data-related projects, it is crucial to dismantle organizational barriers, for example, fragmentation and siloed data mentality, and integrate expertise and knowledge from various departments (Mikalef et al., 2019b).

6.4.2.2 Evidence of Fragmented Architecture from Findings

The findings from Section 5.6.2 reveal a significant challenge related to the fragmented architecture theme, which presents a substantial obstacle to the effective integration of big data analytics into organizational structures. This fragmentation results in duplicated efforts and inconsistencies in data, hindering the organization's ability to collaborate and leverage data for shared business objectives.

The complexity of legacy systems within the four major banks is identified as a key contributor to architecture fragmentation. Respondents highlighted that maintaining data in separate silos, often driven by the independent operation of systems, particularly in areas like mortgages and credit cards, presents challenges. This segregation leads to a fragmented view of customer data, making it difficult to build holistic customer profiles. Moreover, data storage is dispersed across various platforms, causing data access and centralization difficulties. Compatibility issues further compound the problem, as multiple systems may interpret data differently.

However, some respondents attribute these challenges to a lack of data leadership at the strategic level within the organization and emphasize the importance of aligning data strategy with the broader business strategy to overcome these obstacles and create a more cohesive organizational data view.

6.4.2.3 Comparative Analysis of Findings vs. Literature

The research findings in Section 5.6.2 and the literature in Section 6.4.2 underscore the critical challenge of fragmented data architecture in the banking industry. This challenge represents a significant obstacle to the effective integration of big data analytics into organizational structures and aligns with the observations made in previous studies (Chen et al., 2022; Dubey et al., 2021; Ghasemaghaei et al., 2018). Data fragmentation is consistently identified as a major hurdle organization face when implementing big data initiatives (Mikalef et al., 2019; Soldatos & Kyriazis, 2022). Both the findings and the literature highlight how the complexity of legacy systems and the practice of storing data in isolated or fragmented repositories contribute to this issue, leading to duplicated efforts, data inconsistencies, and difficulties in data access (Ghasemaghaei et al., 2018; Mikalef et al., 2019). Furthermore, data silos are recognized in both sources as a major hindrance to the development of a data-driven culture, emphasizing the importance of top management support in overcoming these challenges (Mikalef et al., 2019). To tackle these challenges, alignment between data strategy and broader business strategy, the implementation of governance structures, and the creation of processes to break down departmental silos are emphasized in both the research and the literature (Awan et al., 2021; Mikalef et al., 2021; Soldatos & Kyriazis, 2022).

6.4.2.4 Conclusion

The findings and the literature underscore the critical challenge of fragmented data architecture in the banking industry, hindering the effective integration of big data analytics. This issue aligns with previous studies and is consistently identified as a major obstacle resulting from complex legacy systems and data silos. To address this challenge, both sources advocate for aligning data strategy with business strategy, implementing governance structures, and breaking down departmental silos. These shared insights highlight the need to tackle fragmented data architecture for successful data management and analytics in the banking sector.

6.4.3 RQ3 – Theme 3: Single-View Architecture

6.4.3.1 Evidence of Single-View Architecture from Literature

A significant challenge the financial industry encounters is acquiring data from a wide range of unstructured and tumultuous sources, encompassing data generated by machines or sensors and extensive collections of public and private data (Soldatos & Kyriazis, 2022). To effectively address this challenge, big data architecture must integrate seamlessly with the organization's support infrastructure (Grover et al., 2018). This integration is of paramount importance to ensure the incorporation of such diverse data into the decision-making process, thereby leveraging the full potential of these valuable data sources (Brandtner & Mates, 2021).

A study by Jha et al. (2020) proved that integrating a big data solution with the organization's legacy systems and data has potential benefits. This integration would provide a profound understanding of big data, enabling organizations to enhance various aspects of their operations, such as business processes, resource optimization, fraud detection, and customer relationship management, ultimately improving customer satisfaction. After successful integration, big data analytics could become the primary source for reporting and analytics. However, Grover et al. (2018) and Soldatos and Kyriazis (2022) noted that many organizations lack a strategic plan for executing big data integration, emphasizing the need for a dedicated big data integration strategy to effectively manage data from multiple sources. The primary challenge identified is the integration of new datasets into existing pipelines. Surprisingly, Jha et al. (2020) note that none of the organizations had implemented a framework for integrating Big Data solutions with legacy systems despite generating reports from legacy and Big Data sources and combining them for final analysis.

According to Mikalef et al. (2019), the organizational culture does not support the implement big data initiatives because existing data silos prevent access to the data essential for developing crucial insights. Mikalef et al. (2019) further suggest that establishing a culture driven by data, where decision-making incorporates a balance between insights derived from data and managerial intuition, necessitates strong backing from top management. It requires the establishment of robust governance frameworks and the implementation of operational protocols and structures that foster the seamless circulation of data within the organization, ultimately eradicating any existing departmental silos (Mikalef et al., 2019b).

6.4.3.2 Evidence of Single-View Architecture from Findings

The findings from Section 5.6.3 reveal that within the banking industry, several key challenges related to data management are due to the data that is all over the place. A significant frustration expressed by most respondents revolves around the fragmented data landscape, with a particular emphasis on the decentralized data management challenge. They stress the importance of a value-driven approach and effective governance while underscoring the lack of data leaders who can bridge the gap between business and IT and the absence of champions to facilitate change management and implementation. This often results in misaligned data projects, incurring unnecessary costs for organizations.

Moreover, respondents noted that decentralized data management leads to a lack of collaboration among different business divisions, resulting in inconsistencies in decision-making and hampering the organization's ability to leverage data effectively in its strategies. The difficulties in creating a unified customer perspective within the organization, driven by many touchpoints and differing interpretations of customer data, were also common concerns. Legacy systems, tailored to specific product lines, posed challenges in harmonizing data for decision-making. Despite these challenges, organizations remained committed to addressing these issues and improving their data management practices.

6.4.3.3 Comparative Analysis of Findings vs Literature

Respondents express frustration with the fragmented data landscape in the findings and highlight the decentralized data management challenge. Similarly, the literature points out that acquiring data from diverse and unstructured sources is a significant challenge for organizations, especially in the financial sector (Soldatos & Kyriazis, 2022). This alignment underscores the common problem of data being scattered and difficult to manage.

The finding's lack of data leaders and champions mirrors the literature's emphasis on a strategic plan for Big Data integration (Grover et al., 2018). Both sources highlight the importance of governance and leadership to manage and leverage data effectively.

According to the findings, decentralized data management leads to a lack of collaboration among business divisions and inconsistencies in decision-making. This is in line with the literature's observation that data silos hinder access to essential data and insights, preventing organizations from making data-driven decisions (Mikalef et al., 2019).

Legacy systems are a shared challenge, as indicated in the findings and the literature. Integrating big data solutions with legacy systems is recognized as a potential benefit in the literature (Jha et al., 2020). However, the lack of a dedicated integration strategy and framework is acknowledged as a significant challenge (Grover et al., 2018).

6.4.3.4 Conclusion

The findings and the literature consistently highlight the importance of addressing the decentralized data challenge, the need for strong leadership and governance, and the difficulties associated with integrating new data sources with legacy systems. These shared insights emphasize the relevance of the findings in the broader context of data management challenges in the banking industry.

6.5 Conclusion of the Academic Argument

Pivotal considerations underscore the impact of big data analytics on data-driven decision-making. The first research question delved into the effective utilization of big data analytics within the South African banking industry, highlighting its practical application. The second research question shed light on the gaps in its successful implementation, revealing areas needing improvement. Lastly, the third research question explored the challenges of integrating big data analytics into organizational structures, recognizing the hurdles that impede seamless incorporation.

These findings collectively unveil the complexities and opportunities surrounding the integration of big data analytics in data-driven decisions within the South African banking sector. Research questions 2 and 3 specifically focussed on the components comprising the tangible and human resource constituents of Section 2.2.1, as highlighted by Mikalef et al. (2018). It was established that for big data analytics to be leveraged effectively within the South African banking industry, strategic alignment with integration into the business ecosystem to extract valuable insights emerges as the crucial focal point. Recommendations highlight the necessity for effective leadership, collaboration with business leaders, and organizational culture to sustain effectiveness in decision-making.

Addressing the scarcity of data skills, fostering value-driven competencies, decentralized data management, siloed organizational structures, and a lack of effective leadership bridging the business-IT gap pose significant challenges to implementing big data analytics for informed decision-making.

7 CHAPTER 7: CONCLUSION AND RECOMMENDATIONS

7.1 Introduction

The research investigated how big data analytics can be leveraged effectively in data-driven decision-making within the South African banking industry. Researchers such as Awan et al. (2021), Chen et al. (2022), Grover et al. (2018), Li et al. (2022), and Mikalef et al. (2021) have advocated for future investigations into the impact of big data analytics on strategic decision-making. They propose a comprehensive consideration of both tangible and intangible resources, including human skills, in addition to the integration of big data analytics. Consequently, the study aimed to delve into the intricate role of big data analytics in shaping data-driven decision-making, exploring their contributions to decision processes, and scrutinizing the influence of organizational culture and leadership on the effective implementation of these analytical tools. It strives to offer insights and recommendations for seamlessly integrating these analytics into the South African banking sector's organizational structures and decision-making processes. It explored the essential elements such as management, technology, skills, and strategic capabilities necessary for effective decision-making while pinpointing significant challenges that may arise.

This chapter marks the conclusion of the study titled ‘Leveraging big data analytics and capabilities for data-driven decision-making in the South African banking industry.' It encompasses presenting research findings and their significance for practical applications and theoretical perspectives. Furthermore, it outlines the constraints of the study and provides recommendations for potential research avenues.

7.2 Principal theoretical conclusions

This study investigated the relationship between big data analytics and capabilities (the influence of leadership, organizational culture, human skills, and technology) and data-driven decision-making. As noted in Section 2.2, the relationship between Big Data Analytics and Capabilities has been researched by Mikalef et al. (2018), acknowledging the significance of integrating big data analytics capabilities and suggesting that tangible and intangible attributes might significantly contribute to levering big data analytics into decision-making. While big data analytics exhibits the potential to translate vast data into valuable insights, its specific strategic value and success in decision-making remain ambiguous (Dong & Yang, 2020; Mikalef et al., 2019b; Awan et al., 2021; Ghasemaghaei et al., 2018; Grover et al., 2018; Rialti et al., 2019).

Thus, this study complements previous scholars and contributes by growing the empirical research of big data analytics relating to decision-making. Notably, Awan et al. (2021), Grover et al. (2018), and Rialti et al. (2019) note this as a substantial knowledge gap. Welcoming the invitation from these scholars, the researcher investigated the impact of big data analytics on data-driven decision-making. This was conducted through exploratory research investigating the effectiveness, implementation, and integration of big data analytics in data-driven decision-making within the South African banking industry.

This study found a connection between big data analytics capabilities and data-driven decision-making. Emphasizing the pivotal role played by leadership and organization, the findings underscore the importance of seamlessly translating data-driven insights into actionable decisions. It brings attention to the critical need for alignment between business and data strategy within the banking sector to maximize the efficacy of big data analytics in decision-making processes. Furthermore, the findings highlight how leadership approaches profoundly influence decision-making by fostering a data-driven and collaborative culture. Legacy systems and data access are still a challenge when it comes to the integration of big data analytics.

The sections below will conclude with each research question's findings and provide a new theoretical framework firmly rooted in quantitative evidence.

7.2.1 Effectiveness of big data analytics on data-driven decision-making

The research uncovered a noteworthy association, emphasizing the importance of aligning a data strategy with the overall business strategy to optimize the efficacy of big data analytics in decision-making processes. Following Mikalef et al. (2021), organizations may face failure if they do not proactively align their business and data strategies with their strategic objectives, making it challenging to achieve specific performance outcomes. Grover et al. (2018) assert that the success and achievement of big data analytics should be integrated into a company's enduring business strategy. While the literature reinforces the importance of aligning business and data strategies, it falls short in delving deeply into potential obstacles and challenges hindering this alignment, a common challenge in practice, as suggested by the findings. This underscores the need for further research to comprehensively explore and address these challenges, focusing on the effective deployment and integration of big data analytics within the broader strategic framework.

According to Mikalef et al. (2019b), successful companies developing a data-driven culture forge a strong connection between their organizational strategy and a formal strategy for analytics, as indicated in section 6.2.1.2. However, the research found that accomplishing these hinges on top management or leadership showcasing a greater emphasis on the role of big data and analytics in decision-making. Shamim et al. (2019) argue that leveraging big data to enhance decision-making poses significant management hurdles. Therefore, effectively managing a big data chain requires firms to build up their big data management and analytics capabilities and capacity (Shamim et al., 2019).

Ghasemaghaei et al. (2018) associate big data with the growing availability of data, which serves as a driving force for adopting data analytics and, as seen in the South African banking industry, with a substantial volume of big data from various transactions. The study found that analyzing data without generating value offers no advantages to an organization, irrespective of the data size, whether vast or restricted, as noted by (Chiheb et al., 2019; Elia et al., 2020). The findings from RQ1: Theme 1 have illustrated that the bank has a substantial amount of transactional data, and if leveraged efficiently through big data analytics, it can generate value when synchronized with the business strategy. This perspective finds reinforcement in the existing literature, exemplified by the works of Suoniemi et al. (2020) and Grover et al. (2018), which underscore the necessity of aligning successful big data analytics integration with long-standing business strategies.

7.2.2 Implementation of big data analytics on data-driven decision-making

The ability to employ big data analytics to formulate strategic decisions based on their results is greatly contingent on the competencies and expertise of the workforce (Mikalef et al., 2018). The study found that companies require high-quality data, suitable information systems, analytical tools, and skilled human analytics talent to generate valuable insights for informed decision-making. These skills encompass technical knowledge, business knowledge, relational knowledge (e.g., communication and collaboration skills), and business analytics knowledge related to data skills.

The findings in section 6.3.1, examining the impact of big data analytics on data-driven decision-making within the South African banking sector, underscore the importance of specific skills and capabilities in organizational success. According to Hung et al. (2020), the banking sector can be regarded as one of the pioneers in embracing data-driven decision-making; the findings have highlighted the evolving data culture within South African banking organizations, with a growing emphasis on data-driven decision-making. It is important to note that even though significant strides have been made, several challenges remain. These are the need for data skills, as indicated by the findings of section 6.3.1, accountability for data quality, data domain expertise, and overcoming cultural barriers to create a truly data-driven organization.

As emphasized by Mikalef et al. (2019b), numerous professional reports underscore the crucial need to foster a data-driven culture within an organization. Attempts to cultivate organization-wide capabilities by applying big data analytics will likely falter without such a culture. The findings reveal a significant correlation with the establishment of a data-driven culture, noting that the success of the South African banking industry hinges on cultivating this culture to forge a robust connection between organizational and formal analytics strategies for successful implementation. The achievement of this goal is heavily reliant on top management or leadership, as illustrated in sections 6.2.2 and 6.2.1, which highlight the importance of aligning business and data strategies. These findings underscore that data and analytics should assume a more prominent role in the decision-making processes.

Furthermore, leveraging insights from big data analytics to enhance business operations is key to unlocking value from big data analytics. Therefore, The findings underscore the significance of active participation by functional business managers in big data analytics initiatives and highlights the need for collaboration with big data analytics experts, including data scientists. Due to the complex and multifaceted nature of analyzing big data, the full potential of big data analytics is realized when a diverse set of skills is employed, and knowledge from various origins is put into action. To maximize the potential of this capability, dedicated big data professionals must collaborate, pooling their individual and collective expertise to make influential decisions (Akhtar et al., 2019; Hagen & Hess, 2021).

7.2.3 Integrating big data analytics on data-driven decision-making

According to Ghasemaghaei et al. (2018), recent research has revealed that numerous companies that invested in big data analytics struggled to leverage these tools' potential benefits fully. While the South African banking industry had made those investments

(Brocchi et al., 2018; Pillay & Van der Merwe, 2021), the findings on integrating big data analytics into the organizational structures revealed that legacy poses a significant obstacle and risk to South African major banks, creating openings for new entrants in the market, therefore not fully leveraging on big data analytics for decision-making. This legacy is rooted in the traditional banking model, which is product-centric, making the shift to a market-oriented approach challenging (section 6.4).

The findings from section 6.4 highlight a common challenge within the banking sector, which is the presence of data fragmentation and silos that hinder businesses from effectively utilizing data to enhance their performance to make decisions. Soldatos & Kyriazis (2022) attest to this and argue that a significant obstacle banks and financial institutions encounter is the division of data among various sources, including databases. Addressing data fragmentation has been highlighted as critical, making it difficult to build holistic customer profiles, the single view of a customer. Soldatos & Kyriazis (2022) propose that data architectures must minimize data fragmentation and leverage isolated data to create integrated big data analytics.

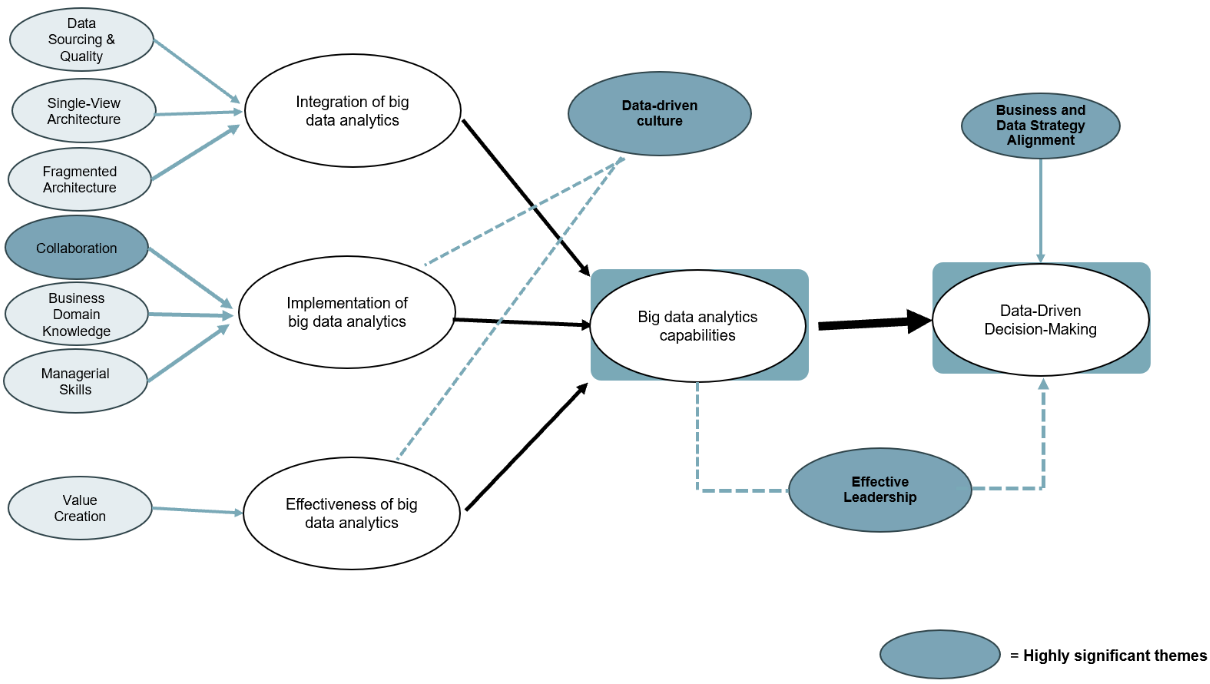
7.2.4 Conclusions

In conclusion, the findings underscore the critical need for aligning data and business strategies, effective data leadership, and fostering a data-driven culture to leverage big data analytics into data-driven decision-making. Despite advancements in data culture within South African banking organizations, challenges persist, including the need for data skills, accountability for data quality, data domain expertise, and overcoming cultural barriers. Active participation by functional business leaders, collaboration with big data analytics experts, and the pooling of diverse skills are highlighted as crucial for maximizing the potential of big data analytics in data-driven decision-making.

To fully unlock the benefits of big data analytics for decision-making in the South African banking sector, it is crucial to address legacy systems and data fragmentation challenges. The findings advocate for concerted efforts to overcome these obstacles, offering a pathway to unleash the full potential of big data analytics.

The framework below, figure 11, is derived from the findings of this study and closes the loop going back to Figure 1, which formed part of the introduction to the research problem in this study.

Figure 11: *Finalised conceptual framework based on the findings.*



Source: Researcher's own

7.3 Research contribution

In Chapter 1, the existing literature acknowledges the pivotal importance of big data analytics in organizations, leading to an increased focus on investigating its impact on strategic decision-making (Awan et al., 2021). Despite the growing body of research and technological progress in big data analytics (Grover et al., 2018), a substantial knowledge gap persists concerning the specific influence of big data analytics and capabilities on decision-making processes (Awan et al., 2021; Grover et al., 2018; Rialti et al., 2019). While the banking industry leads in adopting big data analytics compared to other sectors, it faces persistent challenges in integrating these analytics into its culture and decision-making processes (Hung et al., 2020; Pillay & Van der Merwe, 2021; Brocchi et al., 2018). Therefore, the disparity between adopting big data analytics and its integration within the banking sector underscores an underexplored research domain focused on understanding the obstacles and facilitators in aligning big data analytics with data-driven decision-making processes.

Therefore, the study added value to academia by elucidating empirical relationships related to data-driven decision-making within the South African banking industry amid the era of big data analytics. Consequently, this study made significant contributions to the literature on big data analytics, shedding light on its effective utilization and integration into the decision-making process. Moreover, the research study contributes by uncovering the connections between big data analytics capabilities and data-driven decision-making. The insights from these findings offer valuable guidance to business practitioners, enabling them to make well-informed decisions regarding the optimal use of big data analytics in shaping data-driven decision-making processes.

7.4 Recommendations for management

The research findings outline the necessity for data strategy to be aligned with business strategy, effective leadership, collaboration with business leaders, and organizational culture to sustain effectiveness in data-driven decision-making. However, addressing the scarcity of data skills, fostering value-driven competencies, decentralized data management, siloed organizational structures, and a lack of effective leadership bridging the business-IT gap pose significant challenges to implementing big data analytics for informed decision-making.

- Aligning Data and Business Strategies: Prioritize the alignment of data strategy with the overall business strategy to optimize the effectiveness of big data analytics in decision-making.
- Fostering a Data-Driven Culture: Recognize the pivotal role of top management in showcasing a greater emphasis on the role of big data and analytics in decision-making. Invest in efforts to develop and cultivate a data-driven culture within the organization, as the study highlights its correlation with success in data analytics implementation.
- Enhancing Workforce Skills and Capabilities: Recognize the importance of human skills, data skills, and capabilities identified in the study to implement big data analytics in decision-making effectively. Invest in training and development programs to address challenges related to the need for data skills, accountability for data quality, data domain expertise, and overcoming cultural barriers.
- Promoting Collaboration Across Functions: Encourage active participation of functional business leaders in big data analytics initiatives. Facilitate collaboration between available business managers and big data analytics experts, including data scientists, to pool diverse skills for maximizing the potential of big data analytics.
- Addressing Legacy Issues and Data Fragmentation: Recognize and address the legacy issues rooted in the traditional banking model, which pose obstacles to fully

leveraging big data analytics for decision-making. Develop strategies to overcome challenges related to data fragmentation, data silos, and the division of data among various sources, ensuring integrated big data analytics.

7.5 Limitations of the research

Below are the research limitations for the qualitative study conducted:

- The semi-structured findings in this study focused solely on constructs from the literature review, potentially overlooking other factors influencing the connection between big data analytics and data-driven decision-making.
- The results may lack applicability to other industries or geographic contexts due to the specific focus on the banking sector within South Africa.
- Future studies could explore additional variables for a more comprehensive understanding.
- The potential limitations of this study are associated with the small sample size, particularly concerning the generalizability of the results.
- The researcher's lack of prior training in conducting qualitative research interviews might have affected the outcomes, and their involvement in the data collection process could introduce biases.
- Respondent bias may have impacted personal opinions and interpretations, including varying perspectives on big data and limited insights based on their roles within the company.
- The research did not quantitatively assess improved decision-making, preventing the establishment of a causal link between big data analytics success and data-driven decision-making.
- Moreover, the dynamic nature of the data and technology environment suggests that the research's validity may be restricted to a specific timeframe following its completion.

7.6 Suggestions for future research

Based on the findings, the following are proposed for the future research:

- Case studies, experiments, and longitudinal studies can be undertaken to assess the impact of big data analytics on data-driven decision-making within the South African industry. This will involve testing the significant impact of each success factor on organizational improvement and determining the extent to which each factor contributes to the decision-making.

- Explore the obstacles and challenges that hinder the alignment of business and data strategies, as identified in the study, to gain a deeper understanding of their origins and complexities.
- Explore challenges and opportunities specific to the South African banking industry in leveraging big data analytics by investigating the industry-specific factors that may influence the adoption, implementation, and integration of big data analytics strategies.
- As per section 6.3, it is emphasized that challenges arising from siloed organizational structures need attention to promote collaboration and facilitate data sharing, which is crucial for effective data-driven decision-making. Exploring the impact of siloed organizational structures is recommended.
- Lastly, it is recommended that potential strategies be explored to alleviate challenges associated with legacy systems. The impediment posed by legacy issues inherent in the traditional banking model on decision-making processes and operational efficiency is acknowledged as a hurdle to optimizing data-driven decision-making.

8 REFERENCES

Ahmed, R., Shaheen, S., & Philbin, S. P. (2022). The role of big data analytics and decision-making in achieving project success. *Journal of Engineering and Technology Management*, *65*, 101697. https://doi.org/10.1016/j.jengtecman.2022.101697

Akhtar, P., Frynas, J. G., Mellahi, K., & Ullah, S. (2019). Big data-savvy teams' skills, big data-driven actions and business performance. *British Journal of Management*, *30*(2), 252–271. https://doi.org/10.1111/1467-8551.12333

Awan, U., Shamim, S., Khan, Z., Zia, N. U., Shariq, S. M., & Khan, M. N. (2021). Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. *Technological Forecasting and Social Change*, *168*, 120766. https://doi.org/10.1016/j.techfore.2021.120766

Azungah, T. (2018). Qualitative research: Deductive and inductive approaches to data analysis. Qualitative Research Journal, 18(4), 383–400. https://doi.org/10.1108/QRJ-D-18-00035

Bahrami, M., & Shokouhyar, S. (2022). The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: A dynamic capability view. *Information Technology & People*, *35*(5), 1621–1651. https://doi.org/10.1108/ITP-01-2021-0048

Bell E., Bryman A., & Harley B. (2017). *Business research methods* (2nd ed.). Oxford University Press.

Boldosova, V., & Luoto, S. (2019). Storytelling, business analytics and big data interpretation: Literature review and theoretical propositions. *Management Research Review,* 43(2), 204–222. https://doi.org/10.1108/MRR-03-2019-0106

Bonache, J. (2021). The challenge of using a 'non-positivist' paradigm and getting through the peer-review process. *Human Resource Management Journal*, 31(1), 37–48. https://doi.org/10.1111/1748-8583.12319

Brandtner, P., & Mates, M. (2021). Artificial intelligence in strategic foresight – current practices and future application potentials: Current practices and future application potentials. *The 2021 12th International Conference on E-Business, Management and Economics*, 75–81. https://doi.org/10.1145/3481127.3481177

Brocchi, C., Grande, D., Rowshankish, K., Saleh, T., & Weinberg, A. (2018). *Designing a data transformation that delivers value right from the start*.

Bryman, A. (2012). *Social research methods* (4th ed.). Oxford University Press.

Chatterjee, S., Chaudhuri, R., Gupta, S., Sivarajah, U., & Bag, S. (2023). Assessing the impact of big data analytics on decision-making processes, forecasting, and performance of a firm. *Technological Forecasting and Social Change*, *196*, 122824. https://doi.org/10.1016/j.techfore.2023.122824

Chen, L., Liu, H., Zhou, Z., Chen, M., & Chen, Y. (2022). IT-business alignment, big data analytics capability, and strategic decision-making: Moderating roles of event criticality and disruption of COVID-19. *Decision Support Systems*, *161*, 113745. https://doi.org/10.1016/j.dss.2022.113745

Chiheb, F., Boumahdi, F., & Bouarfa, H. (2019). A new model for integrating big data into phases of decision-making process. *Procedia Computer Science*, *151*, 636–642. https://doi.org/10.1016/j.procs.2019.04.085

Côrte-Real, N., Ruivo, P., Oliveira, T., & Popovič, A. (2019). Unlocking the drivers of big data analytics value in firms. *Journal of Business Research*, *97*, 160–173. https://doi.org/10.1016/j.jbusres.2018.12.072

Dicuonzo, G., Galeone, G., Zappimbulso, E., & Dell'Atti, V. (2019). Risk management 4.0: the role of big data analytics in the bank sector. *International Journal of Economics and Financial Issues*, *9*(6), 40–47. https://doi.org/10.32479/ijefi.8556

Diebold, F. X. (n.d.). *A personal perspective on the origin(s) and development of "big data": The phenomenon, the term, and the discipline* [Working Paper No. 13-003]. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2202843

Diebold, F. X. (2012). *On the origin(s) and development of the term 'big data'* [Working Paper No. 12-037]. SSRN. https://doi.org/10.2139/ssrn.2152421

Dong, J. Q., & Yang, C.-H. (2020). Business value of big data analytics: A systems-theoretic approach and empirical test. *Information & Management*, *57*(1), 103124. https://doi.org/10.1016/j.im.2018.11.001

Dubey, R., Gunasekaran, A., Childe, S. J., Fosso Wamba, S., Roubaud, D., & Foropon, C. (2021). Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. *International Journal of Production Research*, *59*(1), 110–128. https://doi.org/10.1080/00207543.2019.1582820

Elia, G., Polimeno, G., Solazzo, G., & Passiante, G. (2020). A multi-dimension framework for value creation through Big Data. *Industrial Marketing Management*, *90*, 617–632. https://doi.org/10.1016/j.indmarman.2020.03.015

Elia, G., Raguseo, E., Solazzo, G., & Pigni, F. (2022). Strategic business value from big data analytics: An empirical analysis of the mediating effects of value creation mechanisms. *Information & Management*, *59*(8), 103701. https://doi.org/10.1016/j.im.2022.103701

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, *165*, 234–246.

https://doi.org/10.1016/j.ijpe.2014.12.031

Ghasemaghaei, M. (2019). Does data analytics use improve firm decision making quality? The role of knowledge sharing and data analytics competency. *Decision Support Systems*, *120*, 14–24. https://doi.org/10.1016/j.dss.2019.03.004

Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems*, *27*(1), 101–113. https://doi.org/10.1016/j.jsis.2017.10.001

Grover, V., Chiang, R. H. L., Liang, T.-P., & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. *Journal of Management Information Systems*, *35*(2), 388–423. https://doi.org/10.1080/07421222.2018.1451951

Gu, D., Li, J., Li, X., & Liang, C. (2017). Visualizing the knowledge structure and evolution of big data research in healthcare informatics. *International Journal of Medical Informatics*, *98*, 22–32. https://doi.org/10.1016/j.ijmedinf.2016.11.006

Gul, R., Leong, K., Mubashar, A., Al-Faryan, M. A. S., & Sung, A. (2023). The empirical Nexus between Data-Driven Decision-Making and Productivity: Evidence from Pakistan’s banking sector. *Cogent Business & Management*, *10*(1), 2178290. https://doi.org/10.1080/23311975.2023.2178290

Hagen, J., & Hess, T. (2021). *Collaboration for big data analytics: Investigating the (troubled) relationship between data science experts and functional managers*. Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2021.030

Hung, J.-L., He, W., & Shen, J. (2020). Big data analytics for supply chain relationship in banking. *Industrial Marketing Management*, *86*, 144–153. https://doi.org/10.1016/j.indmarman.2019.11.001

Jha, S., Jha, M., O’Brien, L., Cowling, M., & Wells, M. (2020). *Leveraging the organisational legacy: Understanding how businesses integrate legacy data into their big data plans*. MDPI. https://www.mdpi.com/750044

Khanna, S., & Martins, H. (n.d.). *Six digital growth strategies for banks*.

LaValle, S., Hopkins, M., Lesser, E., Shockley, R., & Kruschwitz, N. (2010). Analytics: The new path to value. *MIT Sloan Management Review, 51*(2), 1-25. https://sloanreview.mit.edu/projects/analytics-the-new-path-to-value/

Lehrer, C., Wieneke, A., vom Brocke, J., Jung, R., & Seidel, S. (2018). How big data analytics enables service innovation: Materiality, affordance, and the individualization of service. *Journal of Management Information Systems*, *35*(2), 424–460. https://doi.org/10.1080/07421222.2018.1451953

Li, L., Lin, J., Ouyang, Y., & Luo, X. (R). (2022). Evaluating the impact of big data analytics usage on the decision-making quality of organizations. *Technological Forecasting and Social Change*, *175*, 121355. https://doi.org/10.1016/j.techfore.2021.121355

Lu, J., Liu, A., Song, Y., & Zhang, G. (2020). Data-driven decision support under concept drift in streamed big data. *Complex & Intelligent Systems*, *6*(1), 157–163. https://doi.org/10.1007/s40747-019-00124-4

Lynch, S. E., & Mors, M. L. (2019). Strategy implementation and organizational change: How formal reorganization affects professional networks. *Long Range Planning*, *52*(2), 255–270. https://doi.org/10.1016/j.lrp.2018.02.003

Merendino, A., Dibb, S., Meadows, M., Quinn, L., Wilson, D., Simkin, L., & Canhoto, A. (2018). Big data, big decisions: The impact of big data on board level decision-making. *Journal of Business Research*, *93*, 67–78. https://doi.org/10.1016/j.jbusres.2018.08.029

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019a). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, *98*, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019b). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*, *30*(2), 272–298. https://doi.org/10.1111/1467-8551.12343

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, *57*(2), 103169. https://doi.org/10.1016/j.im.2019.05.004

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and E-Business Management*, *16*(3), 547–578. https://doi.org/10.1007/s10257-017-0362-y

Mikalef, P., van de Wetering, R., & Krogstie, J. (2021). Building dynamic capabilities by leveraging big data analytics: The role of organizational inertia. *Information & Management*, *58*(6), 103412. https://doi.org/10.1016/j.im.2020.103412

Nair, S. (2020). Is Your Business Masquerading as Data- Driven? *Harvard Business Review Digital Articles*, 2–5. https://hbr.org/2020/05/is-your-business-masquerading-as-data-driven

National Treasury South Africa. (2021). *A safer financial sector to serve South Africa better*. https://www.treasury.gov.za/twinpeaks/20131211%20-

%20item%202%20a%20safer%20financial%20sector%20to%20serve%20south%20africa%20better.pdf

Nisar, Q. A., Nasir, N., Jamshed, S., Naz, S., Ali, M., & Ali, S. (2021). Big data management and environmental performance: Role of big data decision-making capabilities and decision-making quality. *Journal of Enterprise Information Management*, *34*(4), 1061–1096. https://doi.org/10.1108/JEIM-04-2020-0137

Pillay, K., & Van der Merwe, A. (2021). Big data driven decision making model: A case of the South African banking sector. *South African Computer Journal*, *33*(2). https://doi.org/10.18489/sacj.v33i2.928

Rialti, R., Marzi, G., Ciappei, C., & Busso, D. (2019). Big data and dynamic capabilities: A bibliometric analysis and systematic literature review. *Management Decision*, *57*(8), 2052–2068. https://doi.org/10.1108/MD-07-2018-0821

Shamim, S., Zeng, J., Khan, Z., & Zia, N. U. (2020). Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technological Forecasting and Social Change*, *161*, 120315. https://doi.org/10.1016/j.techfore.2020.120315

Shamim, S., Zeng, J., Shariq, S. M., & Khan, Z. (2019). Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view. *Information & Management*, *56*(6), 103135. https://doi.org/10.1016/j.im.2018.12.003

Sanchez, J. I., Bonache, J., Paz-Aparicio, C., & Oberty, C. Z. (2023). Combining interpretivism and positivism in international business research: The example of the expatriate role. *Journal of World Business*, 58(2), 101419. https://doi.org/10.1016/j.jwb.2022.101419

Saunders, M., Lewis, P., & Thornhill, A. (2015). *Research methods for business students* (7th ed.). Pearson.

Soldatos, J., & Kyriazis, D. (Eds.). (2022). *Big data and artificial intelligence in digital finance: increasing personalization and trust in digital finance using big data and AI*. Springer International Publishing. https://doi.org/10.1007/978-3-030-94590-9

Stobierski, T. (2019). The advantages of data-driven decision-making. *Harvard Business School.* https://online.hbs.edu/blog/post/data-driven-decision-making

Suoniemi, S., Meyer-Waarden, L., Munzel, A., Zablah, A. R., & Straub, D. (2020). Big data and firm performance: The roles of market-directed capabilities and business strategy. *Information & Management*, *57*(7), 103365. https://doi.org/10.1016/j.im.2020.103365

Tabesh, P., Mousavidin, E., & Hasani, S. (2019). Implementing big data strategies: A managerial perspective. *Business Horizons*, *62*(3), 347–358. https://doi.org/10.1016/j.bushor.2019.02.001

Tseng, H.-T. (2023). Customer-centered data power: Sensing and responding capability in big data analytics. *Journal of Business Research*, *158*, 113689. https://doi.org/10.1016/j.jbusres.2023.113689

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wang, Y., Kung, L., Gupta, S., & Ozdemir, S. (2019). Leveraging big data analytics to improve quality of care in healthcare organizations: A configurational perspective. *British Journal of Management*, *30*(2), 362–388. https://doi.org/10.1111/1467-8551.12332

Yasmin, M., Tatoglu, E., Kilic, H. S., Zaim, S., & Delen, D. (2020). Big data analytics capabilities and firm performance: An integrated MCDM approach. *Journal of Business Research*, *114*, 1–15. https://doi.org/10.1016/j.jbusres.2020.03.028

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Appendix A: Ethical Clearance Approval

GIBS ETHICAL CLEARANCE APPLICATION FORM 2023/24

G. APPROVALS FOR/OF THIS APPLICATION

When the applicant is a student of GIBS, the applicant must please ensure that the supervisor and co-supervisor (where relevant) has signed the form before submission

STUDENT RESEARCHER/APPLICANT:

29. I affirm that all relevant information has been provided in this form and its attachments and that all statements made are correct.

Student Researcher's Name in capital letters:	
Date:	01 Aug 2023
Supervisor Name in capital letters:	SUZANNE MYBURGH
Date:	01 Aug 2023
Co-supervisor Name in capital letters:	
Date:	01 Aug 2023

Note: GIBS shall do everything in its power to protect the personal information supplied herein, in accordance to its company privacy policies as well the Protection of Personal Information Act, 2013. Access to all of the above provided personal information is restricted, only employees who need the information to perform a specific job are granted access to this information.

Decision:

Approved

REC comments:

Approved

Date: 07 Aug 2023

Appendix B: Interview Consent Form

Dear [Participant's Name],

My name is ……. and I am a Master's student in Corporate Strategy with the Gordon Institute of Business Science affiliated with Pretoria University, Johannesburg.

As part of my studies, I must undertake a research project, and I am exploring how Big Data Analytics can be leveraged for Strategic Decision-Making in the South African Banking industry. The study will investigate the factors that contribute to the success of big data and aims to comprehend the circumstances in which big data analytics capabilities can bring benefits and enhance strategic decision-making. This research will involve conducting interviews to gather valuable insights and perspectives from experienced professionals like yourself who are actively involved in strategic decision-making within the banking industry. By sharing your experiences, knowledge, and opinions, you will contribute to advancing our understanding of how big data analytics can enhance decision-making in this context.

Please note that participation in this study is completely voluntary. You have the right to decline participation or withdraw from the study at any time without any negative consequences. Confidentiality is of utmost importance in this research. All information provided by participants will be treated with strict confidentiality. Your identity will be kept anonymous in any reports or publications that arise from this research. Only the research team will have access to the data collected, and every effort will be made to ensure that your personal information remains confidential and secure.

Our interview is expected to last an hour (60 minutes). If you agree to participate in this research study and are comfortable with conducting the recorded interview on Microsoft Teams, Google meet or Zoom, please reply to this email to acknowledge your agreement. Additionally, if you have any questions, or concerns, or require further clarification, please do not hesitate to contact my supervisor or me. Our details are provided below.

Thank you for considering participation in this research study. Your willingness to contribute is greatly appreciated.

Name	**Researcher:**	**Research supervisor:** Suzanne Myburgh
Email:	22029789@mygibs.co.za	Suzanne.myburgh@hotmail.com
Phone:	0832092321	0724069191

Kind Regards,

Signature of participant: ________________________________

Date: ________________

Signature of researcher: ________________________________

Date: ________________

Appendix C: Interview Guide

Research Question	**Interview Questions**
Kick-off question. What is the general understanding of big data and its current situation?	1. Tell me more about your role at your organization.
	2. How long have you been employed by your organization?
	3. Are you a frequent consumer of big data analytics in your organization? Do you use the insights generated from your data for decision-making?
	4. Who else consumes big data – how is big data consumed in the organization - and how do big data projects initiate, kick-off, or commence?
	5. How does your organization see and understand big data analytics?
Research Question 1 How does big data analytics contribute to the effectiveness of data-driven decision-making?	6. Earlier you mentioned that you use big data analytics insights for decision-making, please can you elaborate: How is big data analytics used for decision-making in your organization?
	7. Do you believe big data analytics can be considered a source for decision-making? Please provide your reasoning or justification for your answer.
	8. Do you believe it can add value to the organization? How?
	9. How and to what extent is BD linked to business problems or business targets in the organization? Are industry or business experts – people who truly know the business – adequately brought together with Data scientists?
Research Question 2 How does your organizational culture and leadership impact the successful implementation of big data analytics for data-driven decision-making?	10. Do you think culture has an impact when implementing big data analytics into decision-making?
	11. In your view, what are the specific big data resource requirements to effectively leverage big data analytics into decision-making?
	12. Does a disparity exist between the identified resource requirements mentioned in question 11 and the available big data resources? Kindly provide reasoning to support your answer.
	13. How do you propose that these resource gaps be addressed? Please explain.

Research Question 3 How can big data analytics be effectively integrated into existing organizational structures and decision-making processes to enhance decision-making?	14. How can big data analytics be effectively integrated into existing organizational structures and decision-making processes to enhance strategic decision-making?
	15. What are the challenges that hinder the integration of big data analytics into existing organizational structures?
	16. How do you propose that these challenges be addressed? Please explain.
Research Question 4 What are the key challenges and limitations associated with leveraging big data analytics for data-driven strategic decision-making?	17. How can the quality of insights derived from big data analytics be enhanced for decision-making? Kindly provide an explanation.
	18. What are the challenges associated with leveraging these insights into decision-making? 19. Do you perhaps have recommendations on how we can enhance the effectiveness of big data analytics, with a focus on driving decision-making that positively impacts the overall business strategy

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Appendix D: ATLAS.ti Code Book

Research Question	Theme	Categories
Research Question 1: The effectiveness of big data analytics on data-driven decision-making	Business and Data Strategy Alignment	BDS - Business strategy alignment
		BDS - Business problems not always linked to strategy
		BDS - Solve problem with strategic intent
		BDS - Unproductive data when the business strategy is not aligned to data strategy
		BDS - Agile Business strategies that will accomodate the data strategy
		BDS - Data insights used as to inform strategy
	Leadership Presence	LD - Data leadership in the right place
		LD - Visibility and effective communication from the data leaders
		LD - Analytics be represented in the executive level of the business
		LD - Chief Analytics Officer
		LD - Data leaders who lack the necessary skills
	Value Creation	VC - Reporting purposes
		VC - Solve problem with strategic intent
		VC - Actionable data insights
		VC - Pro-active use of data
		VC - Value created when decisions integrated with DS processes
		Money waisted on data landing
		Data to be measured in the balance and income statements
Research Question 2: Effective implementation of big data analytics on data-driven decision-making	Skills	IMPL - Data leadership skills who poses both business and data skills
		IMPL - Business Domain Knowledge
		IMPL - Data anlytics skills
		IMPL - Graduate programs on data
		IMPL - Equip business with Self Service skills
		IMPL - Upskilling internal employees
		IMPL - Pipelines of data skills to Data Science
	Data Driven Culture	DDC - Organisational learning
		DDC -Data driven culture
		DDC - Data Literacy
		DDC - Information sharing
	Collaboration	COL - Collaborative culture
		COL - Interaction between analytics community and business leaders
		COL - Collaborative effort with business leaders
		COL - Effective communication and interpersonal skills
		Bridge the silo mentality
		Centre of Excellence to bridge the gap
		Data Science as a Research and Development function
		Retain data employees
		Business Navigators
Research Question 3: Integrating Big Data Analytics within existing organizational structures.	Data Sourcing and Integrity	DSI - Data quality
		DSI - Compliance enforced on data sources
		INT - Layers of data systems
	Fragmented Architecture	INT - Fragmented architecture due to Legacy systems
		INT - Data decentralized
		INT - Complexity on the organization architecture
		DSI - Data security
	Single-View of customer	SVA - Quality insights on Single source of data storage
		SVA - Technology integration
		SVA - Central customer analysis
		Compliance enforced on data sources
		Architecture of the organisation