Factors influencing the adoption of big data analytics in the South African financial services industry

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Declaration

I, Siyabonga Mthethwa, declare that this research article is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in Digital Business at the Graduate School of Business Administration, University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

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Signed at Johannesburg

On the 30 June 2023

Abstract

The rapid expansion of big data analytics (BDA) presents significant prospects for organizations across industries, including the financial services sector. This research investigated the factors that influence the adoption of BDA within the South African financial services industry, examining their impact on investment decision-making and the evaluation of post-implementation value.

A comprehensive research framework is employed to accomplish these objectives, combining the Technological, Organizational, and Environmental (TOE) framework with the BDA Adoption model. The TOE framework provides a contextual understanding of technological, organisational, and environmental factors, while the BDA Adoption model specifically focuses on moderating factors such as paradigm shift and organisation's complexity tolerance for big data analytics adoption. Data is gathered from diverse stakeholders in the South African financial services industry through a qualitative approach encompassing semi-structured interviews. Thematic analysis method was used to analyse the data gathered from the interviews.

The findings of this study indicate that organizations characterized by a higher tolerance for complexity are more prone to achieving a seamless transition from the intention of adopting BDA to its successful deployment. This study also found that a combination of factors such as top management support, relative advantage, trialability, human resource, regulatory environment and vendor support did influence investment decision-making collectively. Also, the push from the regulators and the need by financial organisations to improve customer experience led to an acceleration of BDA adoption, which ultimately led to investment decisions being made to meet these objectives.

The outcomes of this research will contribute to the growing body of knowledge on BDA adoption by offering unique insights into the factors specific to the South African financial services industry. Furthermore, the findings will assist organizations operating within this sector in making well-informed decisions regarding BDA adoption, optimizing their investments, and maximizing the value obtained from the implementation of BDA technologies.

Keywords:

Adoption, big data analytics, complexity tolerance, deployment gap, financial service industry

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List of Acronyms

AI	Artificial Intelligence
BDA	Big Data Analytics
BI	Business Intelligence
CEO	Chief Executive Officer
CIO	Chief Information Officer
FSI	Financial Service Institutions
FSRA	Financial Sector Regulation Act
IS	Information Systems
IT	Information Technology
KPI	Key Performance Indicator
ML	Machine Learning
NLP	Natural Language Processing
POC	Proof-of-Concept
POS	Point of Sale
TA	Thematic Analysis
TOE	Technology-Organisation-Environment

CHAPTER 1. INTRODUCTION

1.1 Statement of Purpose

This qualitative research aims to explore factors that influence Big Data Analytics adoption in the Financial Service Industry in South Africa.

1.2 Background of the Study

The South African financial service sector is undergoing a major transformation with new Financial Technology (FinTech) entrants such as TymeBank, Bank Zero, and Discovery Bank and, most notably, the entrance of traditional Telecommunication players like MTN and Vodacom with their mobile money value propositions. In response, the four universal banks (Absa, First Rand, Nedbank, and Standard Bank) have continued to pursue large-scale transformation programs aimed at improving customer experience, digital transformation, new ways of working, and enterprise-wide cost reduction (Camarate & Maritz, 2018).

These large-scale transformation programs have led to noticeable changes in the financial sector, with some institutions scaling down their branch network and ramping up their digital presence by incorporating personalisation features on their mobile applications (mobile apps). These changes can be attributed to the effective use of Big Data Analytics by some of the institutions within the sector (Zhu et al., 2021).

“Big Data refers to any data that, by virtue of its characteristics, cannot be treated in the traditional manner regarding the collection, storage, processing, or analysis” (Armstrong & Lee, 2021, p. 87). Big Data Analytics entails the use of statistical tools and algorithms to extract actionable insight from large volumes of data that are collected from various sources (both internal within the organisation and external), which can be in a variety of formats and can be collated using various methods (i.e., batch processing, near real-time and real-time) (Al-Sai & Abdullah, 2019).

1.3 Research Problem

Extensive research has been done at a global level in areas such as Big Data, Big Data Analytics, and Digital Transformation (Al-Sai et al., 2019; Cabrera-Sánchez & Villarejo-Ramos, 2020; Lutfi et al., 2022; Maroufkhani et al., 2020; Surbakti et al., 2020), and yet there is not much research in identifying factors that influence the adoption of Big Data Analytics in the Financial Services Industry in the context of South Africa. Furthermore, preliminary research shows that the combination of Big Data and Advanced Data Analytics within the Financial Services Industry context in South Africa has not been explored. This research aims to contribute to the body of knowledge by crystalising the factors influencing the adoption of Big Data Analytics in Financial Services in South Africa.

For the purpose of this research, the scope of the financial services industry covers traditional retail banks and insurance firms within South Africa.

1.4 Research Objectives

The objective of this research is to contribute to the growing body of knowledge in the area of Big Data Analytics by:

RO1 Understanding factors that influence Big Data Analytics adoption in the South African Financial Service Industry.

RO2 Understand how these factors influence investment decision-making in Big Data Analytics.

RO3 Understand how the value of Big Data Analytics adoption is measured post-implementation.

The literature review provides a detailed view of the benefits and use of Big Data Analytics.

1.5 Significance of the Study

BDA offers organisations a wide range of opportunities for growth, innovation, operational efficiencies, and improved customer experiences (Kangelani & Iyamu, 2020). However, the factors influencing the adoption of this capability within the South African financial services industry remain unclear. Additionally, there is a lack of comprehensive understanding regarding this capability's impact and measurable value (Pedro et al., 2019).

The findings from this study can provide financial service organisations with a competitive advantage by enabling them to harness the potential of BDA. Through a deeper understanding of the opportunities, challenges, and implications associated with its adoption, organisations can make well-informed decisions, optimise their operations, and differentiate themselves in a rapidly evolving market (Verma & Chaurasia, 2019). Moreover, this research can shed light on the unique challenges specific to the South African financial services industry when it comes to adopting BDA. Factors like regulatory compliance, data privacy concerns, and the availability of skilled personnel may vary in this context (Moraes et al., 2022). The study can offer guidance and tailored recommendations for the South African financial services landscape by addressing these industry-specific challenges.

From a regulatory perspective, the study's findings can inform policymakers and regulators in developing appropriate frameworks to responsibly facilitate the adoption of BDA in the financial services sector. This approach ensures a balanced approach to innovation, consumer protection, data privacy, and ethical considerations, thereby fostering an environment conducive to industry growth and sustainability (Yu et al., 2022).

Lastly, this study serves as a foundational piece for future research and advancements in the field of BDA within the financial services industry. It identifies research gaps, suggests areas for further exploration, and inspires researchers to delve deeper into topics such as machine learning, artificial intelligence, predictive analytics, and real-time data processing in the specific context of South Africa (Baig et al., 2019).

By addressing these aspects, the study contributes to the knowledge base of BDA adoption in the South African financial services industry, enabling organisations to embrace data-driven strategies, foster innovation, and establish a solid foundation for sustainable growth and competitiveness in the dynamic digital landscape (Ajah & Nweke, 2019).

1.6 Delimitations of the Study

As stated, this study focuses on Financial Service Institutions that operate within the borders of South Africa. It is acknowledged that some of the organisations in the Financial Service Sector may have operations outside South Africa; however, the crux of this research is to explore these phenomena within the construct of South Africa.

1.7 Definition of Terms

Table 1.1: Study definitions

Term	Definition
Artificial Intelligence	Artificial Intelligence (AI) refers to systems that mimic cognitive functions generally associated with human attributes such as learning, speech, and problem-solving (Russell & Norvig, 2016)
Big Data	“Big Data refers to any data that, by virtue of its characteristics, cannot be treated traditionally regarding the collection, storage, processing, or analysis” (Armstrong & Lee, 2021, p87).
Big Data Analytics	Big Data Analytics entails the use of statistical tools and algorithms to extract actionable insight from large volumes of data that are collected from various sources (both internal within the organisation and external), which can be in a variety of formats and can be collated using various methods (i.e., batch processing, near real-time and real-time).
Financial Service Institution	Refers to registered financial services providers such as commercial and retail banks, insurance firms, and micro-landers.
Machine Learning	Machine Learning (ML) involves the use of AI algorithms that learn from data in the same way we teach children to learn from data (Armstrong & Lee, 2021).

1.8 Assumptions

The following assumptions are made based on the nature of this research:

- The participants are subject matter experts in their respective fields within Financial Service Institutions (FSI).
- The participants provide accurate data based on their knowledge and expertise.
- The research anticipates that some participants might have biased views based on their areas of specialisation and level of seniority within their organisation.

1.9 Chapter Outline

Chapter 1 outlines the purpose of the study and presents the research problem and objectives. The significance of the research is also outlined.

Chapter 2 provides an in-depth literature review on essential components of Big Data Analytics, namely Big Data and Data Analytics, and how these components are integrated and used in Financial Services. The theoretical framework, replicated in this study, explores the "combined Technology-Organisation-Environment (TOE) and Big Data Adoption model" (Walker & Brown, 2019, p.8). The proposed propositions follow the rationale for adopting the TOE and Big Data adoption model.

Chapter 3 outlines the research methodology, research instrument, and data collection process for this study that be used in this research. Population sample, limitations, and ethical considerations are also covered.

Chapter 4 presents the findings from research interviews that were conducted with data, IT and business practitioners from various financial institutions within South Africa.

Chapter 5 unpacks the discussion and interpretation of insights that were obtained from the findings in Chapter 4. The discussion and interpretation are compared and aligned to academic literature to ensure the credibility of the findings.

Chapter 6 completes the study by integrating the findings with the research objectives set out in the first chapter. Recommendations, limitations, and suggestions for future research are also outlined.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

This chapter provides a literature review on Big Data Analytics, the evolution of the South African Financial Service Industry and explores factors that influence Big Data Analytics Adoption. Furthermore, this research aims to replicate and extend the original case study titled "Big data analytics adoption: A case study in a Large South African telecommunications organisation" by Walker and Brown in 2019.

2.2 Components of Big Data Analytics

2.2.1 Big Data

When compared to relational database management systems that many organisations largely use, big data is frequently characterized by three key attributes: volume, representing a significant amount of data; velocity, denoting the speed of data generation and transmission; and variety, encompassing diverse forms of collected data (Salleh & Janczewski, 2016). In addition to these characteristics, Mikalef et al. (2018) included veracity, variability, value, and visualisation.

Finance industry experts define big data as the tool which allows an organisation to create, manipulate, and manage very large data sets in a given timeframe and the storage required to support the volume of data, characterised by variety, volume and velocity (Srivastava & Gopalkrishnan, 2015). Some major areas where big data analytics has been applied in the financial sector are Customer Value Management, Risk Management and Transaction Analysis (Srivastava & Gopalkrishnan, 2015). This observation suggests that financial institutions need to broaden their scope of data to incorporate external data from platforms such as social media, market research agencies and credit bureaus to drive value for the organisation and customers (Contreras Pinochet et al., 2021).

Table 2.1 shows various forms of data that can be ingested into a big data platform:

Table 2.1: Data sources

Internal/External	Source	Description
Internal	Customer/Account Dimensions	Data consisting of customer demographics and product holding. This type of data is usually captured manually and could be prone to human error.
	Transaction Data	Systems-generated data about all customer transactions on various channels such as ATM, Branch, Online, etc.
	Channel Data	Mostly structured data was collected from channels such as ATMs, Point of Sale (POS) devices and online banking Apps. These data consist of audit trail activities, transactions, etc.
	Credit Data	Structured data sourced from credit origination and management systems. This data consists of a historical view of customers' credit portfolios.
	Call Centre Logs	Semi-structured and unstructured data are collected by call centre agents when customers log incidents regarding their accounts or transactions. These datasets consist of queries captured verbatim and unstructured voice recordings.
	Emails	Semi-structured data on emails sent by customers to call centres, relationship managers, or branch

Internal/External	Source	Description
		managers regarding their products or services.
External	Social Media	Unstructured data from the social media platforms such as LinkedIn and Twitter where a financial institution has a digital presence. Big data may be created by handheld devices, social networks, the Internet of Things, multimedia, and many other new applications with volume, velocity, and variety (Tsai et al., 2015).
	Credit Bureau Data	Structured data containing customers' overall credit profile consists of a score and history. Financial Institutions use this data mainly to assess the customer's financial fitness to repay the loan during the application process.

Once these raw datasets are ingested into a big data platform, they do not necessarily offer any business benefit as they do not provide any meaningful context to support business decision-making or provide actionable insight. To achieve this, specific data analytics techniques must be utilised on big data to extract business value – hence the term "big data analytics".

2.2.2 Data Analytics

Data Analytics is a collection of different tool types based on predictive analytics, data mining, statistics, artificial intelligence, and natural language processing (Russom, 2011). It entails using algorithmic mathematics and statistics combined with powerful software and hardware to transform, discover, interpret, and communicate meaningful patterns in data.

Financial institutions are struggling to profit from the vast volumes of data. Banks only use a small portion of the data to generate insights that enhance customer experiences. This is largely attributed to challenges such as (1) too many silos where customer data typically resides in different systems across different business lines, (2) "Time taken to analyse large data sets, shortage of skilled people for data analytics, (3) Big data is not viewed sufficiently strategically by senior management, (4) unstructured content in big data is too difficult to interpret, and (5) the high cost of storing and analysing large data sets and Big data sets are too complex to collect and store" (Coumaros et al., 2014, p.4).

Organisations have become cognisant of the fact that they need to transition from wanting to know what happened yesterday to wanting to know what is happening now, what is likely to happen in future, and what actions they should take to seize the opportunity of mitigating the risk. This type of insight is made possible through the use of AI. The area of AI has been widely researched in academic and business fields; hence various definitions exist. Duan et al. (2019) describe AI as the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks. Russell and Norvig (2016) defined the term AI to describe systems that mimic cognitive functions generally associated with human attributes such as learning, speech, and problem-solving. Both definitions have common themes pertaining to tasks, performance, people and machines, implying that AI's purpose is to programmatically instruct the computer to perform human cognitive tasks with greater accuracy. In the context of AI, these human tasks are grouped into the following five different categories known as AI tasks (Armstrong & Lee, 2021):

- **Natural language processing (NLP)**: is concerned with the ability to teach computers to understand human speech. Social media companies widely use NLP to analyse and extract sentiment from written text.
- **Machine Learning:** this involves AI algorithms that learn from data in the same way we teach children to learn from data (Armstrong & Lee, 2021). Most business use cases deployed in most financial institutions are based on Machine Learning principles. ML has had a considerable impact in the

areas of fraud and compliance, credit scoring, financial distress prediction, Robo-advising, and algorithmic trading (Buchanan & Wright 2021).

- **Machine perception**: which is concerned with the ability to teach computers to see and recognise objects. This involves the ability of computers to perceive and accurately assimilate what is happening in the world around them (Armstrong & Lee, 2021).
- **Affective computing**: entails the ability to teach computers to understand emotions.
- **Automated planning:** This entails the ability to teach computers to plan and execute highly repetitive tasks at a faster pace with great accuracy.

2.2.3 Big Data Analytics

Big data analytics (BDA) is where advanced analytics tools and techniques are used on big data sets to produce actionable insights (Ashabi et al., 2020). Hence, BDA is about two things – big data (which entails sourcing and storing) and analytics (which entails applying advanced analytics and statistical models), plus how the two have teamed up to create one of the most profound trends in business intelligence (BI) today (Russom, 2011).

A study conducted by MIT Sloan Management Review in collaboration with IBM Institute for Business Value on 3,000 executives, managers and analysts working across more than 30 industries and 100 countries found that top-performing organisations use analytics five times more than lower performers (LaValle et al., 2011). Furthermore, the study found that Top-performing organisations were twice as likely to use analytics to guide day-to-day operations and future strategies as lower performers (LaValle et al., 2011). These analytics are made possible by Big Data in conjunction with Data Analytics.

2.2.4 Application of Big Data Analytics in Financial Services

The extensive use of ML tasks in financial services is achieved by leveraging four analytic processes: descriptive, diagnostic, predictive, and prescriptive.

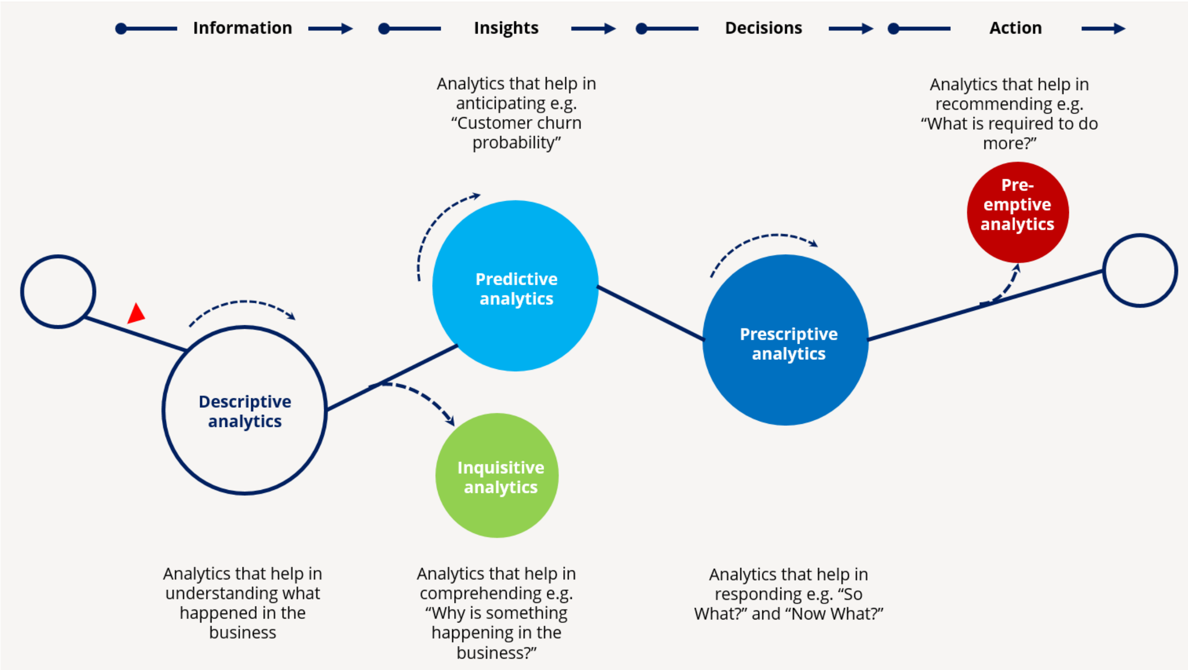

Figure 1: The analytics progression of usefulness

Source: Adopted from Armstrong and Lee (2021).

Figure 1 shows different types of analytics and their usefulness for organisations:

- Wolniak (2023) defines **descriptive analytics** as a branch of data analytics that deals with the examination and interpretation of past data to gain insights into what has happened in a business or organization. It involves collecting, summarizing, and presenting historical data in a way that enables businesses to understand patterns, trends, and relationships. "As a first measure, descriptive analytics allows us to describe simple things about the data, such as averages of variables or distribution (for example, the number of new customers in different geographies).

Descriptive analytics is based on historical data and, therefore, is backwards-looking” (Armstrong & Lee, 2021, p106).

- **“Inquisitive analytics** involves seeking patterns in past data. Statistical techniques, such as correlation and regression, achieve this aim. Inquisitive analytics answers terms such as why, what, what, if, and how. Examples: Based on sales data from previous years during the Christmas holiday, what is the sales projection for TV units for the 2022 Christmas holiday season? What if we increase the price for product x by 5% during the Easter holiday” (Armstrong & Lee, 2021, p106).
- Unlike descriptive analytics, **Predictive analytics** makes use of historic and current data to predict future events. It analyses the current and historical data in order to make predictions about the future by employing the techniques from statistics, data mining, machine learning, and artificial intelligence (Elkan, 2013)**.** Predictive analytics is used quite extensively in credit origination functions to predict the likelihood of a customer defaulting on the loan.
- **“Prescriptive analytics** is the next step beyond descriptive and predictive analytics. Descriptive analytics answers the question “What has happened?” while predictive analytics answers the question “What is likely to happen?”. Prescriptive analytics, on the other hand, seeks to find the best course of action for the future. It can improve decision making and process effectiveness by helping analysts get closer to tying outcomes to specific situations” (Lepenioti et al, 2020, p.12).
- “Finally, **pre-emptive analytics** goes even further into the future and into the possibilities of data usefulness by using big data pattern analysis to suggest courses of action by which future platform operations could be systematically improved. Returning to the customer churn probability example, it is great to predict the likelihood of churn and make machine-specific prescriptions regarding what to do about it. However, far better would be analyses informing affected players (i.e., complements and producers) on how to market, package, and/or price their products better to eliminate issues of revenue loss.” (Armstrong & Lee, 2021, p106).

Many benefits can be realised by FSIs when combining Big Data and Advanced Data Analytics. Mohini and Srivastav (2021) outlined some of the benefits as fraud detection and prevention, segmentation of customers, personalisation of services, customer lifetime value, feedback management, and increased efficiency in operations.

2.3 Theoretical Framework

2.3.1 Big Data Analytics Adoption

A research conducted by Walker and Brown in 2019 titled “*Big data analytics adoption: A case study in a Large South African telecommunications organisation*” identified factors influencing Big Data Analytics adoption by combining the technology, organisation, and environment framework (TOE) with the Big Data Adoption model. The study found that under the Technology theme, five factors, namely “relative advantage, complexity, compatibility, trialability and data quality, were confirmed to influence Big Data Analytics adoption” (Walker & Brown, 2019, p.8). Under the Organisational theme, the study found that factors such as “top management support, human resource expertise, business and information technology (IT) alignment and organisation size were also confirmed to influence BDA adoption” (Walker & Brown, 2019, p.8). Lastly, under the Environmental theme, five “factors were confirmed to influence Big Data Analytics adoption: competitive pressure, data privacy, vendor support, IT fashion and regulatory requirements” (Walker & Brown, 2019, p.8).

Figure 2 shows the combined TOE framework and BDA Adoption model defined by Walker and Brown (2019). A detailed description of factors and their respective propositions are listed in the sections that follow.

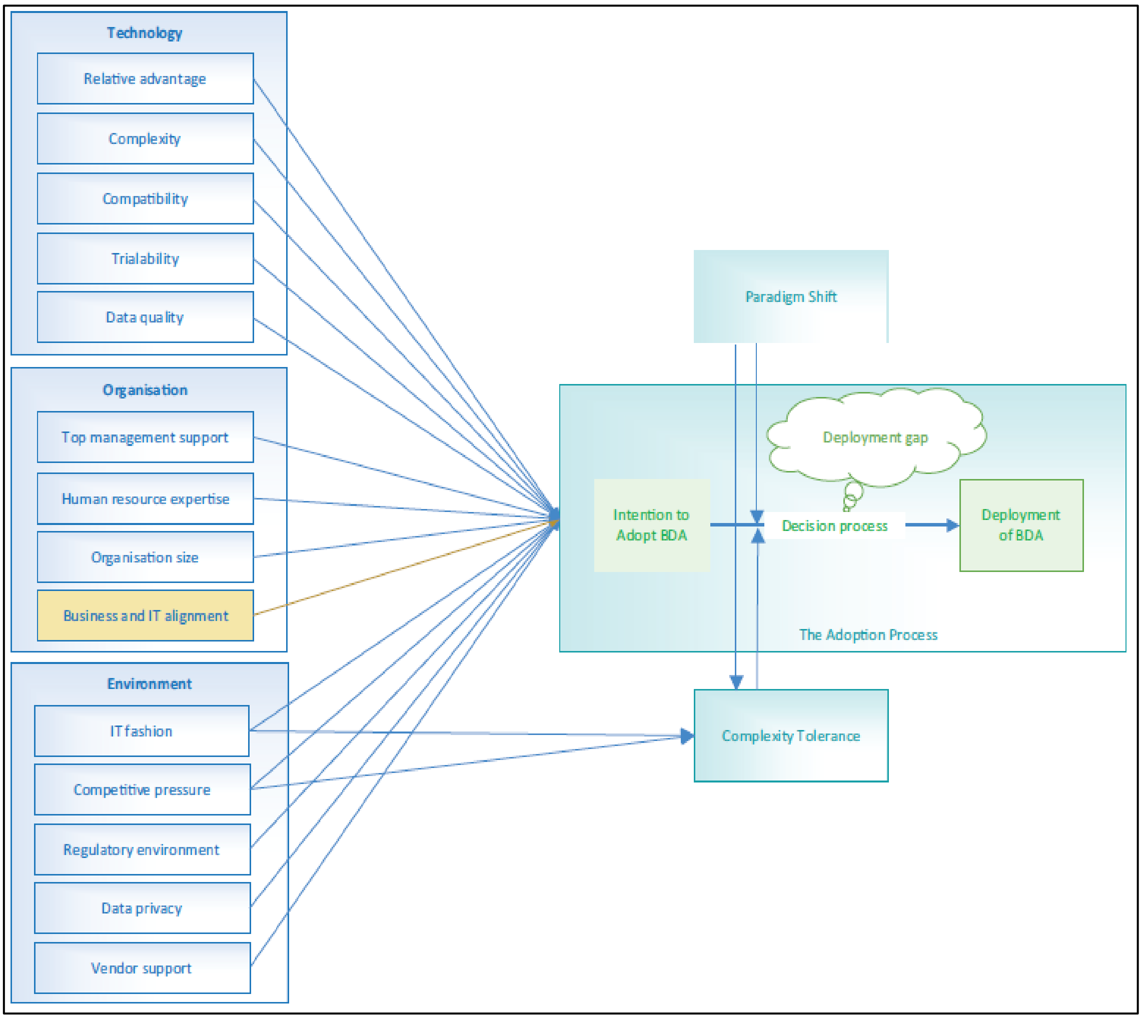

Figure 2: "Final combined technology-organisation-environment framework and Big Data Adoption model"

Source: Adopted from Walker and Brown (2019, p.8).

2.3.2 Moderating Factors

Complexity tolerance: "Complexity tolerance is defined as the extent to which an enterprise can tolerate the complexity in the technology and its implementation process" (Chen et al., 2015b, p.8). Most South African FSIs are plagued by legacy IT systems and complex architectures, which could be attributed to vertical and siloed organisational structures where each business unit has its own IT systems.

The following proposition as defined by Walker and Brown (2019, p.2) is proposed:

> *"P1: The organisation's complexity tolerance influences its ability to move from BDA intention to adopt actual deployment."*

Paradigm shift: "Paradigm shifts are required when there is a fundamental change in a discipline's basic practices and assumptions" (Chen et al., 2015b, p.8). Furthermore, "paradigm shifts contribute to increased complexity of the adoption decision, raising the level of complexity to be tolerated" (Chen et al., 2015b, p.8). The following propositions as defined by Walker and Brown (2019, p.2) are proposed:

> *"P2: The ability to absorb paradigm shifts influences the organisation's ability to move from BDA intention to adopt actual deployment."*
>
> *"P3: The extent of the paradigm shift influences an organisation's complexity tolerance for BDA."*

2.3.3 Technological Factors

Relative advantage refers to "the degree to which an innovation is perceived as better than the idea it supersedes" (Rogers, 2010, p.5). In the context of BDA, "the relative advantage can be measured by aspects such as increased business opportunities, improved customer services, enhanced competitiveness, and the extra value created for customers" (Sun et al.,2018, p.4).

The researcher, therefore, adopts the following proposition as suggested by Walker and Brown (2019, p.2):

> *"P4: Relative advantage influences the BDA adoption process*."

Complexity: Complexity refers to "the degree to which a technology is perceived as being challenging to implement and use" (Rogers, 2010, p.5). Ahmad et al. (2016, p.4) stated that "the lower the perceived complexity of using business intelligence the more likely that business intelligence will be successfully deployed". In the context of BDA, the same notion can be argued. Hence the proposition as suggested by Walker and Brown (2019) is adopted:

"P5: Complexity influences the BDA adoption process."

Compatibility refers to "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (Rogers, 2010, p.5). "Big data should be compatible with both organizational needs and the existing IT infrastructure" (Sun et al.,2018, p.4).

The researcher adopts the following proposition as suggested by Walker and Brown (2019, p.3):

"P6: Compatibility influences the BDA adoption process."

Trialability: "Potential adopters allowed to experiment with a new innovation are likelier to adopt" (Rogers, 2010, p5). Testing and assessing the innovation before adoption will increase the adoption rate (Sun et al., 2018). Ahmad et al. (2016) also stated that trialability of innovations reduces uncertainty around adoption, as organisations can learn by doing.

The researcher, therefore, adopts the following proposition as defined by Walker and Brown (2019, p.3):

"P7: Trialability influences the BDA adoption process."

Data quality: "Big data analytics involves collecting and integrating data from multiple sources. Decision-making is affected by the quality of the data" (Walker & Brown, 2019, p.3). "The more relevant, timely, reliable and accurate the data, the more it positively affects decision-making" (Fredriksson, 2015; Malaka & Brown, 2015; Zhu et al., 2016). The researcher adopts the following proposition as suggested by Walker and Brown (2019, p.3):

"P8: Data quality influences the BDA adoption process."

2.3.4 Organisational Factors

Top management support: "For technological innovation to be successful, top management's support is a critical success factor" (Kalema & Mokgadi, 2017, p.267). Top management can play a crucial role in instilling the right culture, mobilising the rest of the organisation to rally behind a specific initiative and by providing relevant resources such as funding to ensure that innovation projects succeed. Hence, the researcher adopts the following proposition as suggested by Walker and Brown (2019, p.3):

"P9: Top management support influences the BDA adoption process."

Human resource expertise: The successful implementation of BDA relies significantly on a combination of advanced technical skill sets and business expertise. Farzaneh et al. (2018) emphasized the necessity for organizations to possess IT skills in response to the digital transformation of the business landscape. Similarly, Fredriksson's (2015) study on BDA implementation failures highlighted the lack of sufficient skills as the primary challenge faced by organisations.

Hence, the researcher adopts the following proposition as suggested by Walker and Brown (2019, p.3):

"P10: Human resource expertise influences the BDA adoption process."

Business and information technology alignment: "The alignment between business and information technology has been a persistent concern in Information technology management" (Kappelman et al., 2014, p.238). This, therefore, suggests that
Business and IT alignment is concern with ensuring that the organization's strategic priorities and operational needs are effectively supported and facilitated by the design and implementation of the IT infrastructure, systems, and processes.

The research, therefore, adopts the following proposition as suggested by Walker and Brown (2019, p.3):

> *"P11: Business and IT alignment influence the BDA adoption process."*

Organisation size: Rogers' (2010) Diffusion of Innovations Theory suggests that the size of a business plays a substantial role in determining the success of implementing innovative technologies. This notion suggests that larger organisations are a lethargic when it comes to adoption when compared to smaller organisation who enjoy leaner structures which promote agility and rapid adoption of innovations.

The researcher, therefore, adopts the following proposition as suggested by Walker and Brown (2019, p.3):

> *"P12: Organisation size influences the BDA adoption process."*

2.3.5 Environmental Factors

Competitive pressure: Competitive pressure entails the influence exerted by competitors to remain up-to-date and embrace new technologies (Nedev, 2014, p.13). Additionally, external stakeholders contribute to this competitive pressure, thereby impacting the strategic choices and operational effectiveness of organizations. The extent of BDA usage is likely influenced by such competitive pressures from competitors and the external environment (Lautenbach et al., 2017, p.27). Furthermore, it can be inferred that competitive pressure increases the tolerance for complexity (Chen et al., 2015b, p.8). Hence the researcher adopts the following propositions as suggested by Walker and Brown (2019, p.4):

> *"P13: Competitive pressure influences the BDA adoption process."*
>
> *"P14: Competitive pressure influences an organisation's complexity tolerance for BDA."*

Data privacy concerns: "Since many organizations store Big Data in the cloud environment, the security of their data is a critical issue and is an essential antecedent for Big Data adoption" (Farzaneh et al., 2018, p.3). "The BDA characteristics such as volume, velocity and variety contribute to the unique threats that magnify the challenges for managing BDA security compared to traditional data environments" (Salleh & Janczewski, 2016, p.3).

Therefore, the researcher adopts the following proposition as defined by Walker and Brown (2019, p.4):

> *"P15: Data privacy concerns influence the BDA adoption process."*

Vendor support: "One of the significant obstacles faced in BDA is the need for a blend of advanced statistical, analytical, and machine learning skills, which may not be readily accessible within every organization" (Kalema & Mokgadi, 2017, p.263). This need places a dependency on consultants, thus resulting in diminished project control, escalated expenses, and increased time commitment. For this reason, the researcher adopts the following proposition as suggested by Walker and Brown (2019, p.4):

> *"P16: Vendor support influences the BDA adoption process."*

Information technology fashion: “Information technology fashion can be considered the ‘hype’ around a technology pedalled by vendors, consultants, the media and so on” (Chen et al., 2015b, p.7). As such, it is classified as an environmental factor. According to Chen et al. (2015b), the influence of IT fashion on an organization's adoption of BDA and its capability to handle complexity is comparable to the impact of competitive pressure. Therefore, the researcher adopts the following propositions as suggested by Walker and Brown (2019, p.4):

> *“P17: Information technology fashion influences the BDA adoption process.”*

> *“P18: Information technology fashion influences an organisation’s complexity tolerance for BDA.”*

Regulatory requirements: “Regulatory compliance requirements place mandates on organisations and requires them to report accurate information to the market” (Lautenbach et al., 2017, p.27). Regulatory compliance is a significant concern for financial services institutions (FSIs) as they handle sensitive customer information.

For this reason, the researcher adopts the following proposition as suggested by Walker and Brown (2019, p.4):

> *“P19: Regulatory requirements influence the BDA adoption process.”*

2.4 The Rationale for Replicating the Combined TOE & Big Data Adoption Framework

In order to achieve the research objectives, the theoretical framework approach mentioned above was replicated and expanded upon to investigate the factors influencing the adoption of BDA in the South African Financial Services Industry. This is largely due to the fact that both industries share similarities in key areas such as IT System complexities and organisation size and design. Most importantly, factors influencing BDA adoption in FSI in South Africa have not been explored.

A replication study is a deliberate repetition of an index study in whole, part, or conceptually. It provides a means to assess the reliability, validity, and/or generalisability of previous findings or theories (Bouter & Riet, 2021). The existing research on the adoption of BDA primarily focuses on examining adoption intentions during the initial stage, while there is limited attention given to understanding the adoption decision stage that ultimately leads to deployment (Chen et al., 2015b). Additionally, the TOE framework falls short in unpacking the paradoxical phenomenon where, despite big data being a significant technological disruption comparable to the rise of the internet, actual big data deployments remain scarce (Chen et al., 2015b). To address these gaps, this research aims to explore the factors influencing the adoption of BDA in the South African financial services industry by replicating the “combined TOE framework and the Big Data Adoption model” proposed by Walker and Brown (2019, p.2).

Like their global counterparts, South African Financial Institutions are highly regulated and have a defined set of financial performance metrics that are used to measure performance in key areas such as profitability, credit, liquidity, and operational efficiency. This posits that Big Data Analytics plays a crucial role in enabling financial institutions to implement proactive measures in key areas such as Credit Risk, Fraud, Customer Attrition, Product Recommendation and Personalisation of Service.

2.5 Conceptual Framework

Figure 3 shows a graphical representation of the conceptual framework which is derived from the theoretical framework to address the objectives of this research.

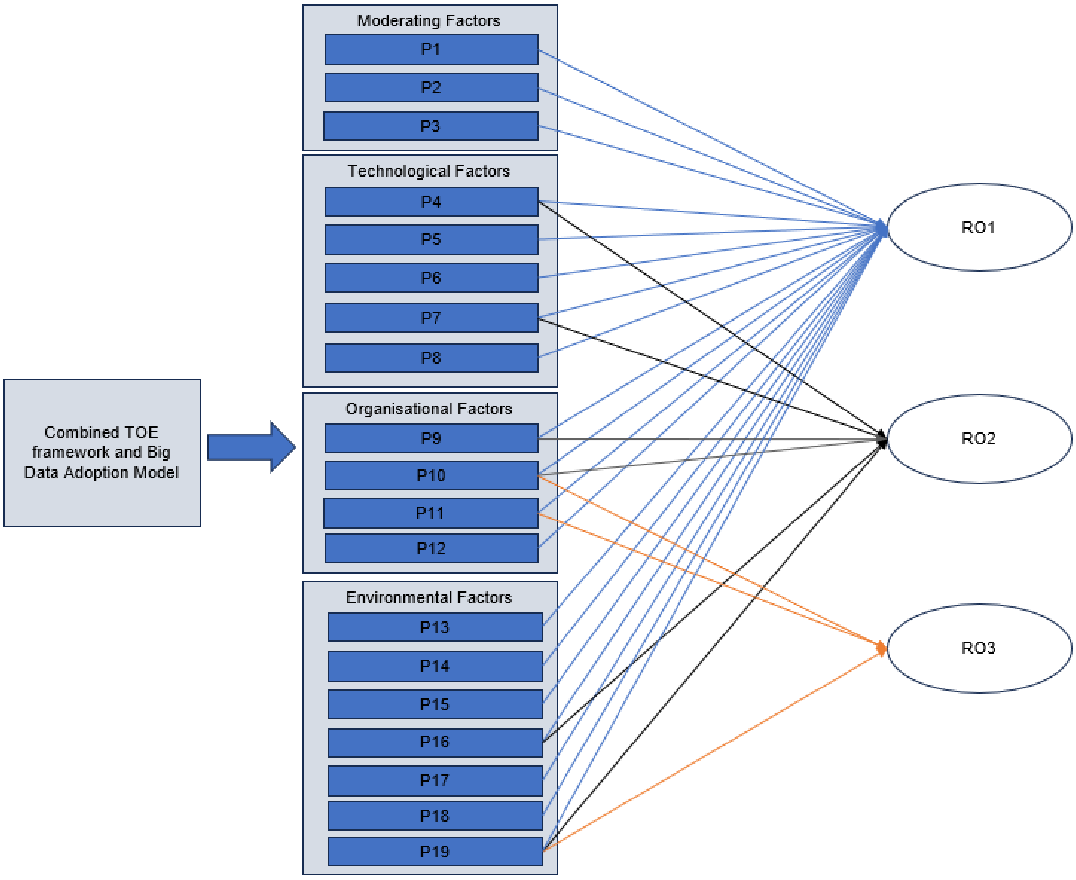

Figure 3: Conceptual framework for the study

Relevant propositions from the combined TOP framework and Big Data Adoption Model have been identified and aligned to appropriate research objectives to aid in exploring factors influencing BDA adoption in the financial sector.

2.6 Chapter Summary

The literature review shows that using Big Data Analytics in FSI greatly benefits all key stakeholders, namely customers, employees, and shareholders. Big data analytics help financial institutions target customer segments at micro levels by combining a variety of data, such as behaviour patterns of the customers, demographic variables, and sentiment analysis from social media (Bhuvana et al., 2016).

This study aims to explore factors influencing the "adoption of big data analytics in the South African financial services industry". This can be achieved by replicating the integrated TOE-BDA model as defined by Walker and Brown (2019, p.2).

The following propositions were replicated from a study done by Walker and Brown (2019) and adopted to fulfil the objectives of this study:

“P1: The organisation’s complexity tolerance influences its ability to move from BDA intention to adopt actual deployment.”

“P2: The ability to absorb paradigm shifts influences the organisation’s ability to move from BDA intention to adopt actual deployment.”

“P3: The extent of the paradigm shift influences an organisation’s complexity tolerance for BDA.”

“P4: Relative advantage influences the BDA adoption process.”

“P5: Complexity influences the BDA adoption process.”

“P6: Compatibility influences the BDA adoption process.”

“P7: Trialability influences the BDA adoption process.”

“P8: Data quality influences the BDA adoption process.”

“P9: Top management support influences the BDA adoption process.”

“P10: Human resource expertise influences the BDA adoption process.”

“P11: Business and IT alignment influence the BDA adoption process.”

“P12: Organisation size influences the BDA adoption process.”

“P13: Competitive pressure influences the BDA adoption process.”

“P14: Competitive pressure influences an organisation’s complexity tolerance for BDA.”

“P15: Data privacy concerns influence the BDA adoption process.”

“P16: Vendor support influences the BDA adoption process.”

“P17: Information technology fashion influences the BDA adoption process.”

“P18: Information technology fashion influences an organisation’s complexity tolerance for BDA.”

“P19: Regulatory requirements influence the BDA adoption process.”

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Research Approach

This study utilises a qualitative approach in line with the original research upon which it is based. Qualitative research describes an event in its context and is useful for investigating complex, new or relatively unexplored areas (Jack & Clark, 1998). It provides a means to study the complex world in a meaningful way and aims to answer the "how" and "why" of a certain phenomenon (McCusker & Gunaydin, 2015). This approach is best suited for this research as it seeks to describe, understand, explain, or interpret human perceptions, behaviours, or views around factors that influence BDA adoption in FSI. Furthermore, qualitative research values the research participant's experience and can offer valuable insight into the settings and situations in which they work (Aspers & Corte, 2019).

The methodology and instrument applied in the original case study be adopted and extended to cover the Financial Services Industry within the South African context. The original study was conducted using a qualitative methodology, where interviews were semi-structured and less formal (Walker & Brown, 2019). Adopting this approach enable effective collection and analysis of insights from various participants who are subject matter experts within their respective organisations.

3.2 Research Design

The literature review shows that using Big Data Analytics in FSI greatly benefits all key stakeholders. However, reviewing the literature for this study, it cannot be determined that the factors influencing BDA adoption in the FSI in South Africa have been empirically explored. In such a scenario, a phenomenology design is ideal. The focus of a phenomenological study is in uncovering and interpreting the inner essence of the participants' cognitive processing regarding some common experience (Worthington, 2013, p. 3). In the case of this research, the phenomenon that the researcher sought to understand was to explore factors influencing the adoption of big data analytics in the South African financial services industry.

While the original study was based on the use case design, which focused on a specific South African telecommunication organisation, this research adopts a phenomenological design approach due to the following reasons (Lester et al., 2020):

- To elucidate the meaning of participant's experience on the factors influencing the adoption of BDA.
- To ensure adequate coverage of the FSI sector to provide a substantial contribution to the growing body of knowledge on the topic.
- To provide a balanced view from all spheres of the FSI sector.

Furthermore, the researcher sought to adopt an inductive approach as it offers flexibility to explore the phenomena while allowing the themes to emerge from analysis that was conducted on data collected from participants. The purpose of this approach is to allow the result to emerge from the frequent, significant themes discovered in the raw data without applying any structured methodology (Jabreen, 2012, p. 170). The researcher found this approach appropriate as it offers a pathway to acquiring a comprehensive and all-encompassing understanding of a phenomenon by scrutinizing data without preconceived notions.

3.2.1 Approach

This research adopted an inductive approach to extract deeper insight from the data (Young, 2019). The advantages and disadvantages of the chosen research design method are listed in Table 3.1.

Table 3.1: Advantages and disadvantages of a qualitative approach

Advantages	Disadvantages
Ease of collecting in-depth insight	Some participants might find the interview lengthy.
Questions can be clarified if the participant requires more context	The sample sizes involved in qualitative research are usually small
The truthfulness of participants can be measured	Prone to bias
Flexibility	Key salient points could be missed due to lengthy responses from participants
Allows for speculative investigations into areas that researchers feel are useful.	

3.3 Data Collection Methods

Data be collected through a series of face-to-face interviews with relevant participants. However, a provision be made for participants who prefer to engage using online meeting platforms like Microsoft Teams, Zoom or Google Meet. This is to accommodate those participants who have moved to other provinces or prefer to maintain social distancing. This encouraged greater participation, leading to a rapid collection of accurate and reliable data.

The interviews ran for an average of sixty (60) minutes to ensure that participants had enough time to provide detailed responses to questions. The interview guide in Appendix C guides the interview process.

3.4 Population

3.4.1 Population

The scope of this research covers the financial services industry, which consists of retail banks and insurance firms. The population that has been identified as relevant to this study consist of participants in the roles:

- Senior Executive (Chief Executive Officers, Chief Financial Officers, and Chief Information Officers),
- Executives (Chief Data and Analytics Officers, Chief Digital Officers, or Chief Data Officers),
- Managers (Functional heads, such as Head of Credit, Head of Analytics or Head of IT and Cloud), and
- Senior Specialist (Data Scientists, Data Engineers, Cloud Specialists).

3.4.2 Sample and Sampling Method

In this research, purposive sampling was the main sampling method (Rahi, 2017). Also known as judgmental, selective or subjective sampling, purposive sampling relies on the judgement of the researcher when it comes to selecting the units (e.g., people, cases/organisations, events, pieces of data) that are to be studied (Rai & Thapa, 2015, p 5). This method is better suited for this exploratory research primarily because it necessitates a targeted selection of participants with specific expertise crucial for comprehending and effectively addressing the challenges at hand.

Also, the snowball sampling method was used to invite more participants in the same sector and level as the primary participants. This method is applied when it is difficult to access subjects with the target characteristics (Naderifar, et al, 2017). In this method, the existing study subjects recruit future subjects among their acquaintances (Naderifar, et al, 2017).

Due to the demanding work schedules of participants of this study, the researcher was able to secure interviews with other participants through referrals from participants who had successfully completed contributed to the research.

3.5 The Research Instrument

A semi-structured interview method was used in this research, and the interview questions were guided by the topics identified during the literature review. The instrument used during data collection consists of open-ended questions designed to stimulate discussion and encourage participants to express their views freely (Ghauri et al., 2020). These open-ended questions were compiled in response to the overarching conceptual framework that is set out in Chapter 2.

See Appendix C for a comprehensive research instrument.

3.6 Procedure for Data Collection

The preliminary interview plan was to be conducted on a face-to-face basis. However, participants who preferred to engage using virtual meeting platforms such as Microsoft Teams, Zoom, or Google Meet were accommodated accordingly to improve participation. The discussion points be structured around three main questions. However, they are open-ended to encourage additional variables/drivers to be brought to the fore that may not have been outlined in the literature review (Brough, 2019).

3.7 Data Analysis Strategies and Interpretation

All key data points (such as transcripts, voice and/or video recordings) that be collected during in-person or online interviews using virtual meeting platforms were verified, organised and stored accordingly to enable a thematic analysis (TA) process (Linneberg & Korsgaard, 2019). All voice recordings from interviews be transcribed into text format using Microsoft Word. TA is the method for analysing specific knowledge production concepts (Holton, 1973) and a qualitative measure for cognitive complexities (Winter & McClelland, 1978).

The TA method consists of the following six phases as defined by Braun and Clarke (2015):

- **Familiarisation**: Data analysis is facilitated by in-depth knowledge of and engagement with the data set.
- **Coding**: A systematic process of identifying and labelling relevant features of the data.
- **Searching for themes**: The search for a theme is not simply one of 'discovery'; the themes are not waiting to be uncovered by an intrepid researcher.
- **Reviewing themes**: The researcher pauses the process of theme generation to check whether candidate themes exhibit good behaviour.
- **Defining and naming theme**: Witting theme definition and selecting theme name to ensure conceptual clarity of each theme and provide a roadmap for the final write-up.
- Writing a report: The researcher weaves together their analytics narrative.

This study's chosen data analysis approach is Big Q, which refers to qualitative research conducted within a qualitative paradigm (Kidder & Fine, 1987).

3.8 Possible Limitations and Challenges of the Study

- Respondent bias is expected, especially at the Executive level, where participants might find it uncomfortable to admit that Management support is still lacking.
- The researcher had no formal training to facilitate interviews at this level. This could have a negative impact on the data collection and the outcome of the study.
- Due to the lengthy interview guide, the quality and credibility of the responses might be compromised.
- The availability of some participants was a challenge because of work commitments.
- Online interviews were negatively affected as power load shedding persisted.

3.9 Quality Assurance

3.9.1 Transferability

Transferability refers to the degree to which the results of qualitative research can be transferred to other contexts or settings with other respondents (Bitsch, 2005). The findings of this research can be applied to another context.

3.9.2 Dependability

All artefacts, such as recordings of interviews with participants, transcripts, analyses and conclusions, be stored in the cloud to ensure safety and ease of access for authorised users. These artefacts are kept safe if they are needed for auditing or authorised by third parties (Noble & Smith, 2015).

3.9.3 Credibility

To ensure that the data collected during interviews reflected the participants' experiences, the interview transcripts and the research report were made available to participants (Wood et al., 2020). Furthermore, participants were given an opportunity to either agree or disagree with the transcripts.

3.9.4 Conformability

Conformability can be defined as the degree to which the results of the inquiry could be confirmed or corroborated by other researchers (Baxter & Eyles 1997). The way in which key data points (such as interview recordings, transcriptions and final data analysis) are stored enables seamless data lineage to further prove that this study's final analysis and conclusions are based on facts.

3.10 Ethics Implications

Ethical considerations can be defined as a systematic approach wherein a researcher seeks informed consent, ensures participant anonymity, effectively communicates the purpose of the study, refrains from deceptive practices, and maintains strict confidentiality throughout the research process (Caruth, 2015). Data collection only commenced upon receipt of Ethics Clearance Approval; see Appendix D.

The study participants received a participation information letter, as presented in Appendix A, which comprehensively detailed the purpose, objectives, confidentiality measures, and interview options. Moreover, participants provided their consent for interviews by signing the participant agreement form, displayed in Appendix B, thereby authorising the researcher to proceed with the interview process (Arifin, 2018).

3.11 Chapter Summary

This chapter unpacked details around processes and guidelines regarding the data collection method, population for this study, sampling method and research instrument. Also, challenges pertaining to the limitations of this study and measures for quality assurance were discussed in detail.

CHAPTER 4. PRESENTATION OF FINDINGS

4.1 Introduction

This chapter presents the findings of the research. The empirical data was obtained by conducting a qualitative analysis of 10 semi-structured interviews with employees from the financial service industry.

The findings are presented in the following format:

- the profile of the participants,
- the relevance of empirical data, and
- the nineteen (19) propositions for the research are categorised under moderating, technological, organisational, and environmental factors.

This format of presenting the findings related to the propositions is aligned with the study's conceptual framework.

4.2 Profile of the Participants

The research study participants were employees of the financial service industry, which consisted of retail banks and insurance firms. The population that was identified as relevant to this study consisted of participants in the roles of senior executive (Chief Executive Officers, Chief Financial Officers, and Chief Information Officers), executives (Chief Data and Analytics Officers, Chief Digital Officers, or Chief Data Officers), managers (Functional heads, such as Head of Credit, Head of Analytics or Head of IT and Cloud), and senior Specialist (Data Scientists, Data Engineers, Cloud Specialists).

Table 4.1: Profile of participants

Participant code.	Role	Years in field
PAT1	Head of data analytics in an organisation	20 years
PAT2	Chief Data and Analytics Officer	14 years
PAT3	Group Data and Analytics Program Head in one of South Africa's top four banks	Almost two decades
PAT4	Wealth cluster manager in a bank (using data for insurance purposes)	20 years
PAT5	Head of Platform Engineering for a bank	20 years
PAT6	CIO of data analytics and AI and Head of data engineering	Approximately 25 years
PAT7	Data Scientist for the Marketing team	Seven years
PAT8	Heady of Data Analytics and IT	18 years
PAT9	Data engineer and Cyber security	About eight years
PAT10	Head of Data Engineering and Business Intelligence at a leading bank in South Africa	18 years

4.3 Relevance of Empirical Study

The word list from Atlas.ti 22 was used to determine the relevance of the empirical data and the alignment of data across all interviews with the purpose of the study (Figure 4). The most dominant words of the study were organisation, data, analytics, business, technology, adoption, complexity, skills, and influence. These words were prevalent across all interviews and aligned with the study. The relevance of the empirical data and interviews is essential for the credibility and rigour of the findings (Guetterman, 2015).

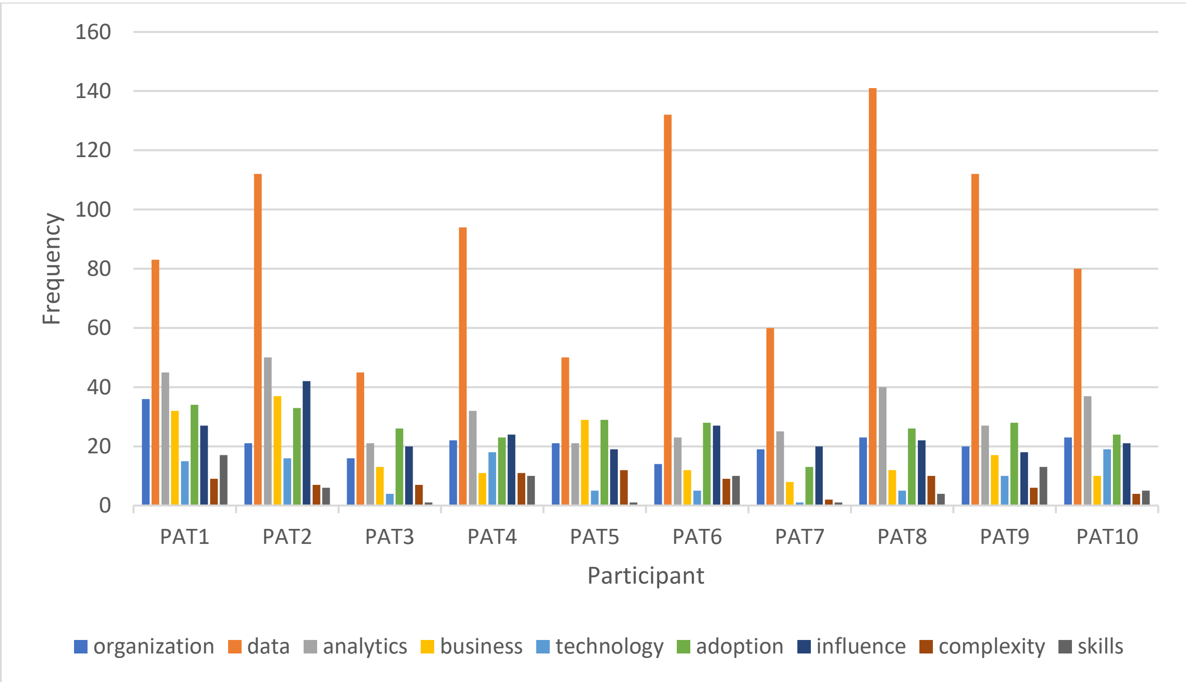

Figure 4: Dominant words

4.4 Findings Related to the Research Propositions

4.4.1 Moderating Factors

Moderating factors comprise complexity tolerance and paradigm shifts, which are the extent to which an enterprise can tolerate the complexity in the technology and its implementation process and the changes required when there is a fundamental change in the basic practices and assumptions in a discipline, respectively.

4.4.1.1 Complexity Tolerance

Proposition 1: The organisation's complexity tolerance influences its ability to move from BDA intention to adopt actual deployment.

One participant highlighted the challenge of moving away from existing investments in capabilities related to big data analytics. They argued that having already invested time, resources, and manpower in the current capabilities, it becomes difficult to transition to new capabilities. This viewpoint suggests resistance to change due to the significant investment made in the current system.

> *"Because you've had lots of investment in these capabilities to move away from that investment, you are restricted; you cannot have a clean slate. You've already layered; you have bodies or people that support that capability that you have, that old capability that you have. So, it's just; it becomes difficult to move away from what you've invested in for a long time, for many years, to this new capability."* (PAT1)

While another participant emphasised the importance of aligning data strategies with business goals and objectives, the participant suggested that it is essential to establish initiatives that drive the realisation of benefits and monetisation. They also mentioned the need to help teams understand the relevance of these initiatives and how they should be implemented within the organisation.

> *"So being able to take that and link your data strategies initiatives to the business goals and objectives, and then putting in place some key initiatives that you need to drive or execute to realise those benefits or monetisation. And then helping those teams then understand how that fits into their world and how that inception, adoption and execution should play out in the organisation. So that's a continuous work in progress across different teams in different stages of maturity."* (PAT3)

Another participant raised concerns about complex data governance and external factors that can hinder the achievement of goals in the big data field. They specifically mention regulatory factors like the Protection of Personal Information (POPI), which imposes restrictions on collecting customer information without proper consent. This viewpoint suggests that external factors and regulations can pose obstacles to the effective utilisation of big data.

> *"If you're in big data, you have complex data governance, and you have the macro industry that might hinder you from meeting your goals. The regulatory things like POPI sometimes can limit us in getting the customer information because you must now get the consent to collect that information that you always had into the database or the data warehouse."* (PAT10)

Overall, while there are areas of agreement among the participants, differing viewpoints also shed light on different aspects of complexity tolerance and the adoption of big data analytics.

4.4.1.2 Paradigm Shift

Proposition 2: The ability to absorb paradigm shifts influences the organisation's ability to move from BDA intention to adopt actual deployment.

One of the major paradigm shifts experienced by some organisations was the shift in the business model due to the convergence of industries brought up by BDA. For example, PAT1 mentioned that their organisation was shifting towards being a platform business, and their industry (service industry) was converging.

> *"I think I would say more positively because we are shifting to, to your point, the service industry is kind of converging. We see a convergence in the service industry. So, then, our organisation specifically has been talking about becoming a platform business, which is to enable, obviously, powered by this data and analytics capabilities."* (PAT1)

This sentiment is further echoed by PAT2, who stated that some of the shifts included being realistic in what their organisation could and could not do and thus resulting in partnerships with other organisations in FinTech that were thought to understand emerging technologies better than organisations who did not specialise in this area of expertise.

> *"I think that the paradigm shifts, shifts that we've had to make is, we've had to be realistic about what we can and cannot do and what that meant is that where we feel like it's not a space that we understand or we are good at, we partner with FinTech who understand the emerging technologies and understand that, you know, there's changes around."* (PAT2)

However, some organisations did not view the changes in their organisations as paradigm shifts. They simply felt that their organisations were just finding better ways of doing things given the tools that they had. For PAT3, their view was that the new technology did not replace their old systems and old ways of doing things but that the new tech and tools allowed organisations to build on their existing systems, thus allowing for growth and transformation.

> *"So using the data that we collate through our menu offerings in the bank and building some actionable insights out of it, and showing the business the value that can be derived has been not a paradigm shift but a different way of thinking*

about platform and data analytics and that platforms don't replace the old existing technologies and systems that we've had before, but that you can build on top of them. You can still extract the information from the core systems working together with these, I would say, data platform technologies that we've adopted." (PAT3)

For other organisations, security was the most important aspect for them and their clients, especially because they were financial institutions. This resulted in these organisations adopting BDA and other technology to ensure the way they handle their customer's data is secure.

> *"There are various aspects; obviously, security as a financial institution is the main thing. So, you know, that's something that they always want to cover, making sure the way that we deal with this new technology is secure, as data loss is a big thing for any institution."* (PAT9)

Proposition 3: The extent of the paradigm shift influences an organisation's complexity tolerance for BDA.

In this response, PAT1 highlighted the struggle faced by their organisation in adopting big data analytics. They mentioned that the organisation is being forced in this direction but acknowledged the challenge of shifting legacy systems and cultural norms.

> *"I think we, we've struggled, to be honest. So, it's not like it's been easy. We are forced; our hands are forced, and we need to go in this direction. Okay. But on the other hand, you have this legacy and culture that you need to shift. So, for me, I think it's more cultural shifts that we've struggled with to be able to cross to what we want to do. So, culture has been one piece that has kind of really slowed us down."* (PAT1)

While PAT2 emphasised the influence of different business pillars within the organisation on the adoption of big data analytics, the participant explained that the varying levels of maturity, skills, and growth across the different pillars impact their appetite and readiness for adopting big data analytics. Furthermore, they mentioned that some pillars, characterised by stability, are more open to coping with the challenges of adopting big data analytics. In contrast, others in a growth phase may face more difficulties.

> *"We have three different business pillars, and each of our business pillars is at a very different maturity, skill, or maturity level. So that means that the way we manage each of those business pillars can be different. So, the appetite could be different between each pillar because of where we are from, from a business maturity or growth perspective. So that does influence how we adopt. So, you will find some of the pillars are open or have the appetite to cope with these productions because we have a very stable business, plus others we feel are still very still in that growth phase. We're still quite stable."* (PAT2)

On the other hand, PAT6 acknowledged the positive understanding and support for adopting big data analytics within their organisation. However, they highlighted the challenge of securing funding and acquiring the necessary skills to enable the adoption process. They pointed out that companies are more willing to invest in software solutions like Salesforce (CRM) or cloud services but are hesitant when it comes to funding the data platform.

> *"The understanding and the support to do it and to adopt it are great. The funding and the skills from a human perspective to enable it is where the problem lies. People are very easily adaptable to spending money on software. Yeah. Like Salesforce. Yes. Or MuleSoft or cloud solutions. But as soon as you bring that funding conversation to the data platform, that's when the people go, no, but it can't be that expensive."* (PAT6)

While security concerns around data privacy in the cloud-based data architecture have been noted, the actual deployment of these technology solutions is not at an acceptable level.

> *"So, the intention has been there, and the adoption has been there. I think the actual deployment of some of the solutions is not 100% yet ready or where we would like it to be. So, for example, the cloud has its own constraints regarding data privacy. So, it is not as simple as just throwing all your data in the cloud. It doesn't work like that. It still sits on a server somewhere. You know, just to get through the red tape to fully implement some of these solutions is what is so busy at the moment."* (PAT8)

4.4.2 Technological Factors

4.4.2.1 Relative Advantage

Proposition 4: Relative advantage influences the BDA adoption process.

PAT1 highlights the advantage of this approach by emphasising that they can avoid the typical emotional challenges and lengthy procurement processes that often accompany such transitions. By moving to the cloud, they are able to reach their desired destination more quickly and at a lower cost. Finally, PAT1 describes this transition to the cloud as an "enabler." This suggests that the move to cloud computing has provided them with opportunities and advantages previously unavailable. It implies that the cloud has facilitated their goals and objectives, making it a positive and beneficial change for the organisation.

> *"As an organisation, we've decided that we want to go cloud, and because we started that journey, we can then move some of these data analytics capabilities or data architecture into the cloud immediately without necessarily having to go through the motions and going through a lengthy procurement process to get to our destination. We get to our destination quicker and cheaper. So for me, I think it's been more an enabler."* (PAT1)

This participant emphasises the importance of understanding and believing in the perceived advantages of the chosen approach. They mention that in order to understand these advantages, one needs to buy into the perceived benefits from the start. This suggests that a belief in the potential advantages is necessary to fully appreciate the value of the chosen approach. They highlight the benefits of getting closer to customers, gaining insights, and ultimately increasing revenue. The speaker also acknowledges the need for effective execution to ensure that the anticipated benefits are achieved.

> *"The relative advantage, I mean, you got to buy into the perceived advantages upfront. So I mean, if you, if you really remove all, all the noise, I mean, you would do this to get closer to your customer to provide a better service to your customer, to gain more insights, to know your customer better, that will invariably lead to more revenue, be it via upselling or cross-selling or cross-selling or retention or reduced churn. So, I think the benefits are pretty well defined. It is to actually execute effectively in order to make making sure that you realise those benefits."* (PAT5)

Other participants cited partnerships with other retailers and joint venture initiatives with companies in different sectors through their platform business as opportunities that have been realised.

> *"I think our results somewhat speak for themselves, especially on the ecosystems and platform businesses. Yes. So some of the joint ventures that we've been involved in have definitely known that benefit. So we've done joint ventures in the agricultural industry and another one with. Also, we've started another joint venture business with the retail giant called ShopRite X."* (PAT6)

This participant indicated that the action taken has resulted in cost savings and allowed them to leverage existing resources. It has also improved data quality, ensuring accurate and reliable data. Additionally, the action has enabled central governance of data, providing better control and security measures to protect against threats like data hacking.

> *So that actually helped us in saving costs and helped us again to leverage from what we have already because what is shared is. Then it also made sure that we*

> *have the best data quality, which is one data quality is one of the practices that need to be done, and governance will now we have central governance of data. So, we can also restrict access and answer to the threads, like hacking our data and all that.* (PAT10)

4.4.2.2 Complexity

Proposition 5: Complexity influences the BDA adoption process.

This participant highlighted the challenge of data privacy and the need to balance it with the desire to gain insights and collaborate with other businesses. They emphasise the importance of de-identifying data while still maintaining individual linkages and express a desire to move away from a less focused approach to data usage.

> *"The biggest blocker is data privacy and what we are about to do with certain of the data and the further processing of data. So if you want to do these joint ventures and adoptions and get some additional insights between a financial and a retail business, how do you actually de-identify the data but still have it linked to an individual to come up with a link? We are definitely on a journey where we don't wanna do the "spray and pray" model."* (PAT6)

4.4.2.3 Compatibility

Proposition 6: Compatibility influences the BDA adoption process.

There were mixed emotions and a variety of opinions when it came to compatibility and its influence on the adoption process. However, one theme was prevalent among participants: integrating the new and the old to achieve organisational goals and targets.

PAT1 and PAT8 highlighted the difficulties of integrating new technologies with existing legacy data systems. They acknowledge that this integration process can be hindering and complex, particularly when dealing with outdated technologies. They contrast their situation with newer organisations that have the advantage of starting fresh but recognise the importance of connecting to their past in order to progress into the future.

> *"Because since you have the legacy systems, you have to kind of find a way to integrate these new sets of technologies to the existing ones. So, I think it's a hindrance because these are old technologies that are difficult to integrate, and some of them have kind of run out end of life. Yeah. How you integrate these two technologies complicates your kind of integration layer. So for me, it's a hindrance. Whereas some of the financial services organisations are new, I won't mention their names; they're able to move faster because they have new tech, and everything is much easier to adopt if you are starting everything afresh. But because of the history of our business, it's difficult for us to kind of ignore that history. You have to connect to your past to be able to project yourself into the future."* (PAT1)

> *"Well, like I mentioned earlier, you know, the problem that we had was the legacy of very old data systems and things just being on different platforms. So, I think when it comes to compatibility, that was a huge struggle. Some of the legacy systems have been transitioned to new platforms, but I don't think we are 100% where we would like to be. So, compatibility had an impact."* (PAT8)

While other participants stated that their organisations had built their enterprise architecture around the flexibility, adaptability and scalability of BDA, which has made compatibility seamless with other technologies.

> *"The way we've tried to build our enterprise architecture is around flexibility and adapt and adaptability, and scalability. So, so we haven't found complexities around the compatibility of technology or tools environment. We do find that a lot of tools and technologies that exist can, can really work well in our architecture. So, I think we've done well in that sense that we haven't tried to make it so limiting."* (PAT2)

"I think from, cause like, like from inception, the sort of like tech stack that we have was built around considerations for big data, right? So making it easy to build data pipelines. Make sure we have like all that data available, and make sure we have the analytics part available for that. In this case, as we've been, we've been running with the same sort of tech that we've had from the beginning." (PAT7)

4.4.2.4 Trialability

Proposition 7: Trialability influences the BDA adoption process.

PAT1 expressed the view that investing in technology allowed for testing. They highlighted the benefits of cloud technology and software as a service (SaaS) in providing the ability to test and learn. They emphasised the subscription-based nature of these services, which supports trying out new technology and increasing investment once it proves successful.

"You invest to the extent that allows you to actually do the testing. So, my view is that the new setup allows the invention of the cloud as a service or infrastructure as a service. Software as a service allows you the ability to actually test you, test and learn. So, there's more; I think we have more options to test, and therefore, once it works for you, you can adopt; it's a subscription-based yes. This really supports your ability to try it out, and when it works, you can invest more." (PAT1)

PAT2 agreed with the importance of trial and error. They mentioned that their data engineering team and data architect prioritise using, testing, and doing their homework before entering into partnerships or contracts. They also mentioned the need to consider skills and maintenance requirements for the tools and solutions they adopt.

"If I look at my data engineering team and our data architect, they're very big on trial and error. They want to use, test, and do their homework. So they never ever go into a partnership or a contract on technology if we haven't tried it ourselves.

And also, if we think about it from a skills and maintenance perspective, we need to be able to maintain a lot of these tools and solutions." (PAT2)

PAT4 agreed that trying new technology is driven by existing technology's limitations or failure to meet needs. They suggested that if the current technology is poor or insufficient, it becomes a driving factor to explore alternative tools or solutions.

"So the driving factor for that is that why would you try new technology? Is a, your existing technology is poor, right? So you've got a poor limitation, or it doesn't meet your needs. So that's one of the reasons why you would say, okay, let's look at this tool, or, you know, whatever, it's not meeting your needs." (PAT4)

PAT8 also agreed with the importance of testing and conducting proofs-of-concept (POCs) before adopting new technology. They emphasised the sensitivity of the data involved and the central role of customers. They express caution, highlighting the need to avoid implementing something without proper testing.

"We definitely do a POC before adopting any new technology, but it is important. It is important to test 1st, and you know, I think because it's such sensitive data that you work with. I mean, remember I said our customers are at the centre of it all. So, you do not want to implement something." (PAT8)

PAT7 offered an opposing view, suggesting that the technology itself is not the blocker. They argue that data content, such as data quality, de-identification, and sharing across multiple zones, can complicate big data analytics but not the extraction of insights. This contrasts with the previous perspectives that primarily focus on the technology itself.

"So yes, the technology itself is not the blocker. It's the data content. And is your data content of good data quality? Can it be de-identifiable? Can it be shared across multiple zones? Those type of things complicates big data analytics but get insights from it. No, there's no complexity." (PAT7)

4.4.2.5 Data Quality

Proposition 8: Data quality refers to the relevance, timeliness, reliability, and accuracy of the outputs.

PAT1 emphasises the increased importance of data quality in the context of real-time or near-real-time data processing. They highlight that the need for analytics to make decisions quickly for clients necessitates ensuring appropriate data quality. They strongly believe that data quality is more important in the current scenario.

"I think it's very important because now you're processing data in real-time or near real-time, so you don't have the opportunity to look at the results and go back and correct. Because you need analytics near real-time compared to what we had before, where you actually take a month to process, you could do away with poor quality. But because you need to make the decision now for the client, it's more important to ensure that your data is of appropriate quality. So for me, it's more important." (PAT1)

PAT2 provides a nuanced view of the importance of data quality, stating that its significance varies depending on the use case. They describe their approach to identifying critical data elements and setting tolerance levels. Some data elements are considered critical with zero tolerance for poor quality, while others may allow for a certain level of exception. They mention incorporating this approach into their data quality management and its integration with AI and analytics.

> *"Interesting. Look, it is important. But how important it varies from use case to use case, and I'll explain. So, for example, what we've done is, as in our data quality management, is we've, we've identified what we call critical data element. We've even created what we call tolerance levels around that data. So what that means is that there are part data elements that could be so critical that there's no tolerance for it to be bad if that makes sense, and then it's something elements, we say, look, if there's an 80%, exception data quality score, that we can tolerate that. So what we've done is we've created the sort of tolerance levels scoring into our data quality management solution. And what we are also trying to do is embed that in how we do the AI and analytics. So, for example, what we can do is, instead of it being a limiting factor, well, there are some things where we're saying they're showstoppers."* (PAT2)

PAT6 agrees that data quality is highly important and emphasises its significance in various data-related initiatives, including big data analytics, normal analytics, and data science. They emphasise the need for trust and ownership in data and analytics initiatives.

> *"Yeah, data quality is very much at the top of our agenda. Fifteen years ago, we did a data quality campaign across the bank, and yes, all bad data disappeared. But now, with all the AI stuff and data science becoming so prevalent and big data prevalent, data quality is more important than ever. So yes, data quality is more important than ever before. Also, I think with anything in data and analytics, data quality is a huge, huge factor. It doesn't matter if it's in big data, whether it's in just your normal analytics, data science type of initiative, it doesn't matter as long as it has to do with data, data quality will always be a huge factor. So, what we realised is that trust is a big deal, and it's even bigger when adopting anything that has to do with data and analytics. But at the same time, we realise that trust needs to be accompanied by ownership."* (PAT6)

4.4.3 Organisational Factors

4.4.3.1 Top Management Support

Proposition 9: Top management support influences the BDA adoption process.

PAT1 considers top management support as the single most critical success factor in the adoption of big data analytics. They emphasise that for successful adoption, the business needs to believe in the potential of big data analytics to solve business problems, and without top management buy-in, the chances of success are limited.

> *"I think, for me, that's the single most critical success factor. If you want if I, if I may use the word in, in the adoption of big data analytics, I think the first thing is that big data analytics is coming to solve a business problem. With that in mind, if you don't have business buy-in and if the business does not believe that you're actually going to solve a business problem, then your chances of succeeding or even moving forward are very limited."* (PAT1)

PAT3 also emphasises the significance of top management buy-in and states that it is key for driving the adoption of big data analytics. They mention the importance of aligning data and analytics objectives with the goals set by the CIOs and CEOs and highlight the appointment of specific roles focused on data and analytics at higher levels of the organisation.

> *"Big, big, big rule it has to come from the top, and that buy-in is key. So, and those KPIs that, you know, those owners in the data space and also when they work with the CIOs and the CEOs to agree that, okay, this makes sense, we're prioritising, it's part of the objectives that we drive in within our areas. It's quite key. And, you know, we've appointed particular data and analytical roles to be able to sit at those levels."* (PAT3)

PAT6 agrees that top management support is crucial for adopting data and analytics initiatives. They believe there is a direct link between top executives adopting data and analytics and their teams also embracing these practices. They mention the CEO's and board members' vision as influential factors in driving investment in data initiatives.

> *"It's absolutely key as they're the decision-makers. It is absolutely a big factor. I see it is that the executives that adopt data and analytics or big data and analytics the most are the ones that have teams that also adopt data and analytics. So, there's a direct link, I believe. Also, the great thing about our organisation is our CEO, and our board members have a big vision when it comes to data and analytics. So that is creating a huge influence on the type of initiatives that the businesses have to invest in when it comes to data. So, absolutely, the answer is yes, it's a big influencer for the adoption."* (PAT6)

PAT8 acknowledges the support from top-level management and highlights significant changes in executive appointments within data architecture and IT departments. They also mention the impact made by individuals one level down from CXOs, who recognise the value of analytics and drive changes in areas like cybersecurity.

> *"Well, look, I mean, if I look at the news flashes that come out from top-level management. There have been new executive appointments within Data architecture and IT departments. So there's been some significant changes in those areas. So there's definitely good support from top-level management, but I'd say more, so probably one level down from top management. I don't wanna call them middle management because that's not what they are, but you know, just one level down from CXOs, there is really where things are happening, and they're those are the guys that are seeing the value. And they are really making an impact, and you know, just in another example, so in our cyber security space, we have these huge changes being made there, where they've realised that what is currently there it's just it's being managed a day in and day out but without applying any analytics to it."* (PAT8)

PAT9 firmly agrees that top management buy-in is essential for successful big data adoption. They stress that the drive and support of top management are crucial because they are the ones who lead the organisation.

> *"Yes, a hundred percent. I mean, if you, if your top management is not smart and you're in trouble, right? Because it's a hundred percent. Cause we have to, you know, they're the ones that drive the organisation. So if you don't get their buy-in, then you know you won't. It's, it's a hundred percent, you know, so you need to get their buy-in for, for whatever you, you implementing some the big data, right? Mm-hmm, but yeah. So they're very important."* (PAT9)

4.4.3.2 Human Resource Expertise

Proposition 10: Human resource expertise influences the BDA adoption process.

In terms of agreements, participants generally agree on the importance of human resource expertise in big data analytics adoption. They emphasise the need for the right skills and highlight the challenges related to high demand and limited supply of these skills, as mentioned by PAT1. PAT9 strongly agrees that relevant skills are necessary for implementing a big data environment.

PAT1 emphasises the need to get the people's strategy right to successfully adopt big data analytics. They highlight the importance of having the right skills, culture, and organisation in driving the capability of data analytics. They also mention the high demand and limited supply of these skills, which can pose challenges.

> *"So, one is to get the buy-in. The next thing you need to do is get your people's strategy right, which is, do we have the right skills? Do we have the right culture and organisation in terms of driving this capability? What kind of skills do we need? Do we have the right mix of skills? How do we keep people motivated? Because of some of these, from a data analytics perspective, the demand for*

these skills is still very high. True. And then, the skills are in limited supply." (PAT1)

PAT6 introduces a different perspective by focusing on the time-to-market aspect rather than the adoption process itself. They mention the struggle of not having enough skilled senior data engineers, which can lead to delays in delivering data solutions. They state that this indirectly influences adoption as it can affect the perception of data being expensive or inaccessible when there are delays.

"I wouldn't say it's the adoption process. I would say it's a time to market. So, what we struggle with currently is we don't have a lot of skilled senior data engineers. So what that means then is that business has to be a bit more patient in getting their data solution. Cause the juniors are going through a test-and-learn phase. So they might have the understanding and some of the skills, but when something goes wrong to fix, it takes time. They don't do proper pipelines the first time. Right. So from that perspective, I won't say it influences the adoption per se influences the time to market, which then indirectly can influence the adoption because that's when people say data is too expensive, it takes too long. I don't have access to my data when I want it." (PAT6)

PAT8 acknowledges the presence of clever and eager-to-learn individuals in the organisation, particularly among young employees. They mention that the skills for analytical and business analytics using big data are present. However, they highlight a lack of guidance in certain areas and specifically mention a shortage of skills in cybersecurity across the industry.

"Well, look, I must tell you from my experience, I think we've got some really clever people in the bank. Especially the young people that are coming in at the moment, they are eager to learn - like they got their hands on the new tools everybody is playing around with ChatGPT, yeah, and it is good to see that, you know. So, I think from an analytical point of view and from a business analytics point of view using big data, I think the skills are there. However, I don't think the guidance is there necessarily. But from a cyber security point of view,

there's a lack of skills there which we do not see just within episodes. It's an industry problem." (PAT8)

PAT9 strongly agrees that human resource expertise is a massive factor and essential for implementing anything related to big data. They emphasise the importance of relevant skills in dealing with the complexities of big data and assert that skills are crucial and cannot be compromised.

> *"It's a massive factor. You can't implement anything without the skills. And you know, with all the new tech coming out, and with just big data and the complexities around it, you can't have anything without the skills. You can't implement a big data environment without the relevant skills. So, it's 100% important, you know, you can't, can't be in between."* (PAT9)

4.4.3.3 Business and Information Technology Alignment

Proposition 11: Business and IT alignment influence the BDA adoption process.

PAT1 highlighted the criticality of aligning technology strategy and business strategy. They asserted that misalignment inhibits the adoption of big data analytics, while close alignment enables and accelerates adoption. They emphasise that the misalignment hinders the ability to use tools effectively to address business questions.

> *"I think aligning your technology strategy and business strategy is critical. Yeah. If that is misaligned, then your big data is already sitting in between, and there'll be no perceived value in the outcome. But if the two are closely aligned, it enables big data analytics adoption. So, the way I would answer that question is that if the two are misaligned, it actually inhibits the adoption of big data. If the two are closely aligned, it enables and accelerates the adoption quickly. Cause then you are using the tools to answer the business question. So, for me, the misalignment*

> *inhibits the alignment of the two strategies. I'm talking about information technology and business strategies."* (PAT1)

This is also echoed by PAT9, who also agreed on the importance of alignment and emphasised the need for clear communication lines between business and IT. They mentioned the language barrier and the necessity of communicators working across both domains to facilitate understanding and collaboration.

> *"Yeah, it's got a big impact, you know, there need to be clear communication lines, and you know, IT and business don't speak the same language, often, you do, but you have to have those communicators in the middle that can work across both. Whether it's a techie with good business skills or an exec with some tech background, you need one of those to do it. Otherwise, it's going to be a struggle."* (PAT9)

PAT10 strongly emphasised the need for alignment between business and data analytics. They considered data and analytics as an enablement team for the business, with the purpose of realising business goals. They stress the importance of eliminating any gaps between business and data analytics to ensure effective support for business needs.

> *"A 100% alignment needs to happen because the business is the one that drives the purpose and data and analytics; we are behind the business. So we need to realise the business goals. We are an enablement team for the business to realise its goals. So they need to always be in alignment; they need to always not be in any gap. So if the business is moving at that speed, data and analytics needs to offer more because we do a lot of case studies, we do a lot of case that responds to the business needs because, for example, you will be interested in this, a bunch of customers but who's gonna do it for you to get to make sure that you get those customers. It's gonna be your information technology."* (PAT10)

PAT3 emphasised the role of IT partners and platform partners in the adoption process. They stated that IT partners support and enable the teams by providing the necessary checks, governance processes, and technical assistance. They considered IT partners as integral to the adoption process.

> *"It does because your IT partners and platform partners are critical in the journey, and they have particular tasks to fulfil. So, if you think of Android and you as an app developer, there are certain checks that Android requires you to do and governance and things that you must make sure if you build this app, there are certain rules and regulations, and then they tell you if you meet these rules and regulations and these governance processes, we will make sure that your app can run. So that could be making sure that the app is up to date and the code is correct so your IT partners support you in running the machine and also enabling the teams to play that part. So they are an integral part of the adoption process."* (PAT3)

PAT6 mentioned the communication and understanding gap between business and IT. They described a situation where business demands are not clearly communicated, leading to misunderstandings and unsatisfactory outcomes. They highlighted the need for improved communication and collaboration to bridge the gap.

> *"A lot. Because we are still in the phase where businesses will just throw the demand over the fence, and they'll just say, I want a tree and then go, but what do you really want? An indigenous tree, or do you want a veggie or fruit tree? Must it be watered? Must it be planted deep? Must it recreate itself? So we still have that problem where business throws demand across the wall, and then they wanna step away, and then magic must happen. And then they come back and say, but this is not what I asked for, but I gave you a tree you didn't ask for, for free."* (PAT6)

4.4.3.4 Organisation Size

Proposition 12: Organisation size influences the BDA adoption process.

PAT3 suggested that the influence of organisation size on big data analytics adoption can vary depending on different pockets within the organisation. Some teams may be further along in the adoption journey due to having more data products and established platforms. They believe that while size plays a role, it is more about the impact and ownership of the team. Having a significant impact and strong ownership can lead to better adoption, regardless of the organisation's size.

> *"I guess it depends on different pockets because different pockets of the organisation might be a bit further in the journey because they've got a lot of data products perhaps running on the platform and, others are maybe still coming up. So, it varies. There are teams in areas where they're a bit further in the journey, and then at least they can reach out to those that are a little bit further. Sure, the size does play a role, but it's not usually the size. It's, it's more the impact, and if you have big impact and ownership, your adoption then might be a little bit better than if you have a small team."* (PAT3)

PAT7 expressed the view that organisation size does have a major influence on adoption. They provided an example of their previous experience in a large company where lengthy decision-making processes were required. In contrast, with a lean team and a flat structure, their current organisation allows for faster decision-making and execution. They attribute the ability to quickly get things done to the smaller, leaner team size.

> *"Yeah. I mean, it does have a major influence. Like, the size of my previous company was huge, and we had to go through lengthy processes to get the decisions made, whereas, in my current organisation, which has a very lean team, that's not the case because it is very flat in terms of structure. So, it's easy for people in power to make decisions fast and get the decision down to the*

operational teams to execute. So, yeah, basically, the influence of the team being a bit small and lean is that we're able to get things done quicker." (PAT7)

PAT9 emphasises the massive impact of organisation size on big data analytics adoption. They mention the high cost of big data platforms, which makes it challenging for smaller organisations to set up a comprehensive data platform. They also highlight the manpower required for big data analytics and data engineering, stating that it takes a significant amount of effort, regardless of the size of the organisation.

> *"Yes, massive, because I've seen what big data platforms cost. You're not going to get a 'mom-and-pop shop' that can really set up a data platform. It's expensive. It was really expensive. So it's got a big impact, I think they're slowly but surely changing where you know, you can get, you know, subscription-based things where you're paying per user, you get those, but overall, not and also, if you look at the amount of manpower, it takes to have that whole big data analytics and data engineering, you know, set up, it takes a lot of, it takes a lot of manpower, it's a lot harder to do, and all for smaller size companies, you know, it doesn't necessarily mean that they have fewer data or less analytics to do because they are only, you know, 500 employees, it doesn't really matter. But it takes the same amount of manpower, relatively speaking, to build that environment. So that's got a big impact."* (PAT9)

PAT10 opposed the notion that organisation size is a determining factor in big data analytics adoption. They believe that what truly matters is having the right skills and purpose. They argued that even a smaller organisation with the right skills and purpose could outperform a larger organisation. They used the analogy of an elephant and an ant to illustrate their viewpoint.

> *"I don't think size matters. I think what matters is the skill. If you have the right skill and if you have the purpose, you might be an elephant, but an ant might do better than you. So the size of the organisation doesn't really matter to me. So it's the skill and the purpose."* (PAT10)

4.4.4 Environmental factors

4.4.4.1 Competitive pressure

Proposition 13: Competitive pressure influences the BDA adoption process.

PAT6 presents an interesting viewpoint where one of its leaders does not perceive competitors as threats but rather as opportunities for growth and innovation. They view competitors as potential partners with whom they can collaborate to solve problems. This perspective sees competition as a positive force, driving the organisation to improve and explore joint ventures. However, PAT6 also acknowledges that compliance with regulations poses a challenge, especially when compared to more agile FinTech companies that have fewer regulatory obligations. This indicates a potential opposing view regarding the competitive pressure faced by traditional financial services.

> *"One of our leaders said she doesn't see them as competition or always threats. But she sees them as an opportunity for our organisation to grow and innovate. So, if, for example, we think Ban X is a threat, we go meet them and see how we can do things together and solve the problem. So, she doesn't see them as a threat, which I thought was quite an interesting viewpoint. She them as opportunities to either grow or to innovate better or to make a joint venture. On the other hand, I do think FinTech, because of the nature of their regulation, don't have to comply as much as we as financial services have to, so they can get time to market quicker, which is a challenge for us. If we can have the same rule book by the reserve as the fintech has, we would achieve much more. But just because of the size of the beast, we have to comply with too many governance structures and rules and stuff. So we take long, and then we might lose clients."* (PAT6)

PAT9 expressed a somewhat ambiguous stance on the influence of competitive pressure. They mention the importance of staying competitive and not falling too far behind. While they emphasise the significance of security benchmarking within the financial institution's environment, they express uncertainty regarding the competitive aspect. They suggest that there may be secrecy surrounding the competitive strategies of other businesses, indicating a potentially opposing view on the direct impact of competitive pressure.

> *"Currently, it's got an impact. You know, you have to be competitive, and you can't really fall too far behind. But again, you know, it comes down to the customers as well. You know, you need more we're in the security space. So, You know, so being on top of security is crucial. And, you know, in that sense, the banks are quite, you know, they benchmark, there's a lot of benchmarking within the financial institution's environment to make sure everyone's safe to pretty much to keep the customer safe. But from, you know, from a business point competitive point of view, I'm not sure. I'm pretty sure there's a bit more secrecy there in What is that?"* (PAT9)

PAT10 agrees that competitive pressure matters and highlights the importance of keeping up with what other organisations are doing. They mention the need to collect information and learn quickly to enable functionalities that competitors may be introducing, such as cardless withdrawals. PAT10 recognises the influence of market trends and emphasises the need to adapt to customer demands. Their viewpoint aligns with the idea that competitive pressure drives organisations to stay informed and agile in order to meet customer expectations.

> ***"****You know what? Competitive pressure does matter. You have to be interested in what others are doing out there so that you can keep up with them, because, for example, if they have a better offer that they are busy preparing and you don't know about it, for example, cardless withdrawals, you need to collect information for you to enable that functionality. So if, for example, Bank X is busy making cardless withdrawals, people are, as I told you in the beginning, people are moving with the trends. So we have to also move towards the direction of the trends. So it matters what they're doing. You need to know what they're doing so that we can learn fast and fail fast."* (PAT10)

Proposition 14: Competitive pressure influences an organisation's complexity tolerance for BDA.

PAT1 suggested that competitive pressure can increase the complexity and costs associated with adopting big data analytics. They mentioned the competition for skilled professionals, where other organisations may attract and hire skilled individuals from their organisation, leading to a loss of expertise and the need to rebuild the skill set. Additionally, they mentioned that competitive organisations might be willing to pay higher salaries, which increases costs for acquiring and retaining skilled professionals. This viewpoint highlights the challenges and complexities brought about by competitive pressure in terms of talent acquisition and cost management.

> *"I think they make it. It may make it more complicated. Yeah. I mean, if I look at the competition for skills in itself, yes, you'll be building, you start building, and people will come and steal from you some of your skills because they need the skills, they need the capability. They'll come and dilute that. So, you have to start again. They'll come and pay three, four times the price that you're paying. You'll also go and do the same thing. So, it just makes it more, more expensive and more cost and more complex."* (PAT1)

While PAT2 held the opinion that competitive pressure does not significantly influence their organisation's complexity tolerance for adopting big data analytics, they highlighted that their organisation's strength lies in building long-term relationships with clients based on understanding their needs and providing tailored services and products. According to their viewpoint, the competitive pressure to adopt the latest technologies or have cutting-edge products is not as influential as the emphasis on meeting client needs. They asserted that their organisation's focus on relationships outweighs the impact of competitive pressure.

> *"I don't think it does, to be honest. I'll tell you why because we're a relationship-based organisation. A lot of our clients have been with us for years, 20-plus years. And it's not because we have great products, and it's not because we have the*

state-of-the-art sort of tech. That's not why they're with us. They're with us because of our understanding of their needs and being able to offer services and products that are geared towards those needs. So that's where we pride ourselves. So that's why I'm saying competitive pressure is not a big of an influence per se." (PAT2)

4.4.4.2 Data Privacy Concerns

Proposition 15: Data privacy concerns influence the BDA adoption process.

PAT1, PAT8, PAT9, and PAT10 all highlighted the significant influence of data privacy concerns on big data analytics adoption. They recognised the regulatory requirements such as the POPI Act, compliance processes, and the need for trust and security in handling customer data. These participants shared a common view regarding the importance of data privacy and its impact on analytics practices.

"I think it's one of the top five challenges that we face in our organisation. We are a highly regulated organisation, as you know, so privacy plays a critical role in how we actually shape our analytics. It limits what you can do with what you have internally. However, on the other hand, the integration of external data into the scope for me, as much as it's publicly available, I think you can take advantage of those because it's the people who have put their information out there in the public domain, like social media. But the types of data that we collect and manage internally have to comply with the regulation. Of course, regulations are quite stringent." (PAT1)

"When we hear data privacy, we want to run away. Okay. That is how big an influence it has with the POPIA Act coming into action. If that just made it even more complicated, you know, So I mean, we cannot ingest or look at any data without first going through the legal route and data privacy route. We have to get a signed-off from them. And then, you know, I mentioned other countries that we operate in, and one of the things that is actually a big stumbling block for us is cloud in. Using the data from those countries, I mean some of those countries

are just the governments are not approving any cloud-based application. So, there is just no way that you can do that. So those are the stumbling blocks that we currently have to get passed. So, data privacy definitely has an influence." (PAT8)

"It's got a big influence on data, you know, not necessarily just big data on any data, you know, with the POPIA act. And just, you know, customer privacy and data privacy in general. It's got a, it's got a big impact, you know, it slows down a lot of the developments, but rightly so, you know, you need to make sure that the right processes are in place. Look at the Experian leak, for example, you know, that's a big issue, you know, was it something that could have been done differently, could have had stricter security measures in place to protect it? So, I would say it's got an impact on expanding and moving into new things like big data, but it's also very crucial from a trust point of view, you know, as a financial institution, crowd trust is very important. I think that should come first. So yeah, but as a data practitioner, you know, it's a bit of a headache to go through all the compliance to use the data for good. But, but it's, that's very important from a business point of view." (PAT9)

"It does influence it negatively. I would say because organisations must always be better. I mean, we must be prepared to adopt POPI Act for data privacy purposes now. As I said in the beginning, we used to just have the data freely so you could make it through and cover everyone. But now it's a matter of the customer giving consent. It's a customer being allowed to opt in and opt-out as they please. So, if you so if all the customers opt-out. If you told yourself you have big data, you end up with no big data." (PAT10)

PAT2, on the other hand, expresses a contrasting view, suggesting that data privacy concerns do not significantly influence the adoption of big data analytics. They acknowledge that it adds an additional layer or component to their implementation, affecting factors such as cost, change management, training, and access controls. However, they downplay the overall impact, indicating that it is not a significant concern.

"I don't think it has a huge influence, per se, on the adoption. I think it just adds another layer or another sort of component to our implementation. Which then influences cost, our change management process, our training and our access controls. But you know, there are certain solutions or technologies that are very borderline in their approach. I suppose from a FinTech or from how we adopt things like, you know, social media data, obviously, then data privacy is a big factor. But not really, if I'm being honest. It's not that big of a deal. It just adds on a different layer or component to our existing processes." (PAT2)

4.4.4.3 Vendor Support

Proposition 16: Vendor support influences the BDA adoption process.

PAT1, PAT2, PAT5, and PAT6 all recognised the significant influence of vendor support on big data analytics adoption. They highlighted the importance of reliable vendors, end-to-end support, local presence, and prompt issue resolution. These participants shared a common view regarding the importance of vendor support in successful adoption.

"I think it matters a lot because of the evolution of technology. It's rapid. Yes, you have this today, and tomorrow, so you need some vendors who are kind of, in the long run, not a fly-by-night so that you can actually go this journey with them. Yes, you can spread the risk in terms of having multiple of them, but at least you'll have one that is primary that you want to work the journey with. They clear, if you can see that their vision is very clear in terms of where they want to go to, I think it's good to work the journey with their specific vendor." (PAT1)

"It does, it really does. I think we lean on our vendors to be the ones that understand, you know, the, the technologies and the, and the right solutions that could be good for us. That's the one thing. So we go to them a lot for advice. That makes sense. The second thing is that we have software as a service, which means our agreement with certain vendors is that you support end-to-end. You give us end-to-end support from implementation to maintenance, to upgrades, to advisory, sort of engagement. So obviously, they have a huge influence." (PAT2)

> *"So, vendor support is very, very important. I think once you start looking at a vendor. And you know, from a big data adoption point of view, and you realise that there is not enough support going to be from the vendor, then that is when you need to pull out because either you have to have a situation where they could come to South Africa and spend a couple of weeks here with your team helping you to get the thing into place. Teaching you do training and everything that you need or otherwise, they have to have in-country support somehow to maybe outsource to a different company."* (PAT5)

> *"Especially in our line of business, vendor support is very important. If something goes wrong today, I cannot wait two weeks for a vendor to try and figure it out and come back and tell me what is wrong with the software, well, what is on the roadmap. So for me, it's important that the vendor has a local presence because most of the software we use in our companies is all international. So it's very important for us that there is a local presence in this country that I can access. Also, we are becoming quite deliberate around cost because we do not want to do dollar-based pricing. The vendor must adapt the pricing to the country they are selling to because dollar-based pricing is really killing us. Every time the interest rate goes up, I must find another million rands somewhere."* (PAT6)

However, PAT8 presented an opposing view, expressing dissatisfaction with their vendor support experience. They indicated a lack of alignment between sales representatives and implementation teams, resulting in unmet expectations and difficulties in obtaining additional support. This participant offered a contrasting perspective regarding the effectiveness of vendor support.

> *"So I think I'll just talk in general, you know, I mean, we've had some software that we've been using in our team for a couple of years, and I must say the support from the vendor has not been great. You know, I think, I think the biggest problem really is that the sales guy and the guy that comes to do the POC and implement the solution, they're not the same people, you know, and they don't sync from the same hymn book. So what you think you were getting and what you end up with is not always the same thing in the perfect world, yes, but it doesn't work like that. And then what happens is you have to keep on going back*

to the vendor to get additional support. And now you have to remember there are no companies in South Africa that can really supply you with the software and the tools that you need for big data analytics. These are all American companies. So now you have to have calls late at night, anything from 4:00 o'clock onwards, because we are 8 hours behind and so. So that just puts tremendous pressure on the team and the people that have to work with the vendors." (PAT8)

4.4.4.4 Information Technology Fashion

Proposition 17: Information technology fashion influences the BDA adoption process.

PAT1 and PAT7 shared similar views, emphasising the importance of aligning technology adoption with strategic objectives and use cases. They prioritise tried and tested solutions and strategic alignment over blindly following IT fashion trends.

"I think it's limited. So we, as an organisation, we kind of pick what is kind of tried and tested, which kind of makes us a larger. But it is; we want, we want something that's already been tried and tested, you not trying and testing. But as for our organisation, as long as it's something that will create a specific, that will deliver the specific use case. So it's more use case-based and not following technology trends. As an organisation, we are risk averse, and we're in the business of risk management. So risk management comes top." (PAT1)

"I think for us; it's more of we try and focus on our strategy and our strategic drivers. And then we say, well, based on those strategic drivers and strategic objectives, what are the initiatives that we need to run with and what technology we need to adapt to meet our big data analytics objectives? How do we, with those different things, ensure that we meet our objectives? So, it is in two parts. When we build our strategy, that is always top of mind. So our data analytics strategy is always aligned with our strategic vision. And then second to that is when something does come into the market, we evaluate it. We go through a level of evaluation before we make a decision." (PAT7)

PAT2 acknowledged the influence of IT fashion but stressed the need for evaluation and accountability in decision-making. They share a perspective that aligns with PAT1 and PAT7 in terms of strategic alignment and the importance of considering the organisation's specific needs.

> *"We take it on a, on a need-by-need basis. What I mean by that is if we see, for example, that there's this new technology that might come in, and we'll have a huge impact in the market. We need to evaluate, it'll do an evaluation, and then based on that evaluation, we'll say, okay, what does that mean for us? What do we need to spare ahead? What do we need to fast track or even slow down or even defer? So, the way we do it is through evaluation; we don't just take it at face value. The other thing is because of the regulations; they always ask us the same question. They'll say, well, how are we dealing with emerging trends? How are we adapting to certain emerging technologies? What are our thoughts? What are our plans and so forth? So they also keep us accountable in a way for us to start thinking like that and thinking ahead and thinking about how IT fashion influences us."* (PAT2)

PAT10 acknowledged the influence of IT fashion, particularly in cases where organisations follow market trends or are influenced by external factors such as mergers and acquisitions. They share a project experience where the organisation faced challenges due to sudden technology adoption. This participant suggests that being prepared and considering all aspects are essential when moving with IT fashion trends. They also mention that new functionalities accompany fashion trends, emphasising the need for organisational readiness to adapt.

> *"I can say it does have an influence because some organisations that will just go with the market trends. I once was involved in a project whereby the bank was bought by an outside global bank. Then they said okay, now, because we are the majority shareholders, we need you to start using our technologies. So, I can tell you we face so many challenges. First of all, we're not ready for human resources. We were not ready financially for them to buy as much because when the fashion came, they just wanted to adopt, but that's why you need to make*

sure that you cover all the angles and that you are ready. But otherwise, the fashion as well comes with new functionalities. That's why you need to be ready as an organisation to move with the trends as they move." (PAT10)

Proposition 18: Information technology fashion influences an organisation's complexity tolerance for BDA.

PAT1 believes that information technology fashion does not in any way influence their organisation's complexity tolerance for BDA adoption.

"I would say no, it doesn't". (PAT1)

While PAT2 cited that IT fashion does influence their organisation's complexity tolerance around people and skills from the cost perspective.

"I think where it matters is around people and skills. I mean, I suppose that, that for me is very, it really matters. So if how to explain this? So, I always say to my team, if there's an easier way to do something, let's find it and use it because, at the end of the day, everything has costs." (PAT2)

PAT4 was cautious about adopting IT fashion trends, emphasising the need to evaluate the practicality and integration of new technologies. They stated that their organisation does not hastily jump on fashion trends but focuses on what needs to be done. They mentioned the lack of agility in larger organisations, where implementing new technologies involves navigating through legacy systems and integration factors. Consequently, they cannot simply adopt something just because it's trendy.

"We don't jump on fashion trends, you know, we do; what do we need to do? Obviously, you need to be aware of it and say, okay, this is something we need to gain agility, right? So if you're a big organisation, you can't just go and slap something when it starts using, right? There's a lot of legacy to go through, right? So you need to integrate factors. Does it integrate your idea question? So you can't just jump on it, right? So thankfully, you could look at a loss out a bit of profit share with, for example, crypto, right? So focus structures there, people like, ah, let's jump on it, but most banks weren't jumping on it. They're like, listen, we know what we're doing, and we're gonna do it this way because there's a need for it. And with the crypto world, you had a whole lot of other coins coming out. You had this same Sam, Benton, Freeman FTX, you had, I think these influencers were creating their own North Logan Pole was facing his own crypto zoo, and all failed horribly. People lost millions, right? So instead of us just jumping on whatever is out there, we would rather jump onto what makes sense." (PAT4)

4.4.4.5 Regulatory Requirements

Proposition 19: Regulatory requirements influence the BDA adoption process.

PAT1, PAT2, and PAT10 shared a similar view, acknowledging the significant influence of regulatory requirements on big data analytics adoption. They highlighted the limitations, complexities, and compliance obligations imposed by regulations. These participants recognised the need to align with regulatory demands and consider them as influential factors.

"It's huge, and there are different regulations. We talked about POPIA privacy there. Before these regulations were in place, you could do anything with a specific data set. With those regulations in place, there are very few things that you can do. So, yes, it does limit the use of adoption of big data analytics. Also, when we talk about the best way to really leverage big data is to go cloud, but some of the country's regulations prohibit you from going cloud. And even if you allow, like in South Africa, there are certain things that you cannot take to the cloud, or certain specific data sets that the regulation wouldn't allow you to send to the cloud. So with that in mind, it becomes a bit complex to navigate those

regulations. So the stringent regulations, I think secondly, is the fear factor. The regulators are fearful of the unknown. Because big data analytics is a new phenomenon, hence they are reluctant to support the adoption because they are afraid of the unknowns. So the default answer that the regulator gives you is "no". And then, if you're able to explain and convince them, they will accept. So the first thing is, no, we can't do it, and then you go and argue why you need to do it, and then they will say, okay, you can go ahead." (PAT1)

"It really, I think this is a big one. a lot of regulatory requirements around, you know, from security, data privacy, having single data quality, having the ability to pull insights when living for stress testing. So it's a huge, huge factor for us, and we use their requirements as a way to influence which BDA solutions are built. In fact, a lot of our building on the back of requirement cause the initial, because like I said before, you know, cause of the business model that we had, you know, we maintain what works, we change what doesn't work. But if something gets, you know it stays because it works, why change it? A lot of what the regulators are done is said. Well, now there are certain things we need to new, new requirements, new legislations, sorry, new legislations, new requirements, new regulations that we need to adhere to. And they cannot be done with the current platforms or the current systems that we have. So when it comes to data analytics, we've used that as a means to get the right investments, buy-ins and rollouts. Sure. So to speak." (PAT2)

"It does, hey. Because you know, if you are regulated, you cannot play up to your maximum capacity. You have to always take into consideration to say, does it cover what the regulator says. And again, remember with the regulation we report, time and again. So, I can say it doesn't give you room to play up to a maximum capacity because the regulation is interested in protecting the citizens and our customers." (PAT10)

PAT5 and PAT8 offered perspectives that were partially aligned with the other participants. While they agree that regulatory requirements have an influence, they also introduce additional considerations. PAT5 emphasised the need for compliance and unbiased models, while PAT8 mentioned the varying extent of regulatory requirements based on the type of data. These viewpoints contribute additional nuances to the overall understanding of the influence of regulatory requirements on big data analytics adoption.

> *"It's an important item to consider. So, you need to understand the full implications of what you're trying to do and whether it will have any regulatory impact or requirement. So it, I guess it's, it, it just, it's just another line item to fully get on top of and make sure that you comply with. So, once again, regulation won't stop you from doing something, but it might force you to change your approach; hence it is certainly one of the top items that we always start with and make sure that we're really compliant and that all our solutions are, especially when it comes to machine learning, we make sure that our models are not biased in any way. That's why we work closely with the risk and compliance team."* (PAT5)

> *"I think it depends on the data. I think it depends on the type of data that you're looking at. I mean, if it's customer data, I think you can have a bit of stricter regulatory requirements that you have to adhere to analyse or to get your hands on that data. I think if it's if it's more a run-of-the-mill stuff, so how many staff in the bank has laptops, you know, there's no regulatory requirement really, yeah, to look at that. But it is that big data. No, it isn't. So, you know, that's also the thing big data really comes with huge regulatory implications. So definitely, it has an influence."* (PAT8)

4.5 Chapter Summary

In this chapter, participants' professional profiles and their verbatim responses to interview schedules were unpacked. All participants managed to respond to all questions in the research instrument.

Chapter Five analyses the findings from the interviews and compares them to academic literature with the purpose of addressing the research objectives outlined in Chapter 1.

CHAPTER 5. DISCUSSION OF THE FINDINGS

5.1 Introduction

In this chapter, the insights obtained from the findings in Chapter 4 are discussed and compared to the literature to answer the two objectives set out in Chapter 1.

5.2 Discussion Pertaining to Moderating Factors

Chen et al. (2015b) described moderating factors as the variables that can influence the strength or direction of the relationship between two other variables. They can either enhance or diminish the effects of the main factors being studied. In the context of BDA adoption in South African financial services, some of these variable factors are regulatory environment, top management support, and financial and human resources. In this section, the findings from complexity tolerance and paradigm shift are unpacked and reviewed against the literature.

5.2.1 Complexity Tolerance

Proposition 1: The organisation's complexity tolerance influences its ability to move from BDA intention to adopt actual deployment.

Walker and Brown (2019) define complexity tolerance as the extent to which an enterprise can tolerate the complexity in the technology and in its implementation process.

For most of the participants from the different organisations, the organisation's complexity tolerance was found to influence the intention and adoption of big data analytics in that depending on the organisation's ability to measure the benefits as big data analytics is not readily understood by most organisations. Their ability to measure value could influence adoption; however, their inability to do so may deter organisations from adopting.

In their study, Chen et al. (2015b) emphasised the significance of comprehending the value associated with the adoption of BDA. They posit that when organisations clearly understand the benefits and outcomes that can be obtained through implementing BDA, the decision-making process becomes more rational and informed. This understanding enables decision-makers to evaluate the potential impact, risks, and returns of incorporating BDA into their operations. By considering the value proposition of BDA, organisations can make well-informed decisions that align with their strategic objectives and enhance their overall performance.

Furthermore, other complexities such as existing investments in the form of legacy systems and traditional BI solutions, and business capacity play a role in influencing the adoption as changing investments, especially in human capacity skills within an organisation, was not something organisations could readily do and thus provided another layer of complexity that could influence the organisation's ability and or intention to adopt big data analytics.

Chen et al. (2015b) note that complexity tolerance is contingent on multiple factors, including organisational capabilities to endure complexity, paradigm shifts, and psychological factors. Walker and Brown (2019) cited that the stronger the organisation's tolerance for complexity, the easier it would be to move from intention to actual deployment.

The findings also showed that some organisations have managed to put measures to address complexities in areas such as skills requirements, business and IT strategy alignment and knowledge management to manage changes brought in by BDA. Chen et al. (2015b) defined this approach as a complexity reduction strategy, which includes outsourcing, hiring experienced leadership, clear architecture for divide and conquer, business-IT alignment, knowledge-based approach for technology selection and orchestration, systematic, continuous absorption of complexity via innovation process, and centre of excellence.

Moreover, linking the data strategies initiatives to the business goals and objectives and then putting in place some key initiatives that could help drive or execute the strategies to realise the benefit or monetisation of BDA further added another layer of complexity. Because the different teams within an organisation are at different stages, the intention to adopt, adapt and finally implement BDA in an organisation was experienced as a continuous spectrum where these links are continuously made at different stages, in different teams and at different paces.

Other complexities are not necessarily organisational but come with the updated regulations such as the POPI Act, which is used in the governance of big data, that posed limitations for organisations when intending to adopt, adopt and implement BDA in their organisation. Walker and Brown (2019) affirmed that the foundation of BDA is predominantly unstructured data, and ensuring compliance with regulatory privacy requirements is far more complex and negatively affects BDA adoption in organisations.

5.2.2 Paradigm Shift

Proposition 2: The ability to absorb paradigm shifts influences the organisation's ability to move from BDA intention to adopt actual deployment.

Paradigm shift refers to a fundamental change in the way an organisation thinks about and approaches big data (Chen et al., 2015b).

The adoption of BDA for many organisations has resulted in paradigm shifts at different levels of the organisations, including the various levels of adoption within the organisation itself. One participant cited that one major shift in their organisation was the realisation around what their organisation could and could not do and thus resulting in partnerships with other organisations in FinTech that were thought to understand emerging technologies better than organisations who did not specialise in this area of expertise. Walker and Brown (2019) noted that partnership is influenced by a range of factors, including the organisation's culture, the level of communication between business and IT, and the organisation's willingness to collaborate.

For other organisations, security was the most important aspect for them and their clients, especially because they were financial institutions. This resulted in these organisations adopting BDA and other technology to ensure the way they handle their and the customer's data is secure. This notion is aligned with the views of Walker and Brown (2019) that paradigm shifts increase the complexity of BDA adoption and thus reduce complexity tolerance.

Another participant cited a shift in the business model due to the convergence of industries as a major paradigm shift in their organisation. For example, a participant mentioned that their organisation was shifting towards being a platform business, and their industry (service industry) was converging. The participant further noted that BDA enables this shift. Walker and Brown (2019) posit that the ability to absorb a paradigm shift may influence an organisation's ability to move from intention to actual deployment of BDA.

Proposition 3: The extent of the paradigm shift influences an organisation's complexity tolerance for BDA.

The organisation's ability to deal or cope with the paradigm shift was a huge factor in influencing the organisation's intention to adopt, adopt and implement. This was because, for most organisations, there was a difference in implementation maturity, especially when it came to BDA. Thus, these pillars required different management strategies; this then meant that the different pillars had different levels of appetite and capacity for the adoption of BDA. These varying degrees of intention and capacities highly affected the overall organisation's intention and capacity to cope with the paradigm shifts caused by BDA adoption and, secondly, the organisation's intention and ability to adopt BDA within their organisations.

These observations are further supported by the views that paradigm shifts can increase the complexity of big data technology and thus reduce an organisation's complexity tolerance. When a paradigm shift is not absorbed, many organisations are unable to move to deployment (Chen et al., 2015b)

Some organisations struggled significantly with the paradigm shifts brought up by BDA adoption either because they did not fully anticipate the magnitude of change or were not fully ready for the adoption. However, because of the changes in the industry, they felt they had to adapt quickly in order to participate in their market. These organisations struggled because they had to make legacy (one they built over many years) cultural shifts to become the organisation they wanted to be in this new era of BDA. In a similar study conducted by Walker and Brown (2019), participants noted that the extent of the paradigm shift influenced the organisation's ability to tolerate complexity.

The other reason some organisations are unable to cope with the paradigm shifts that come with the BDA is the financial aspect and cost of the adoption. Buying data and skills to handle data do not come cheap for some organisations. Admittedly, some organisations have not clearly identified the benefits or the value of adopting BDA, especially from a financial perspective. Furthermore, the implementation of the BDA in organisations is a process, and thus, dealing with some of the constraints brought about by the BDA may cause issues for organisations in terms of adapting to the paradigm shifts incurred due to BDA adoption and implementation. Chen et al. (2015b) emphasised the importance of recognising and addressing paradigm shifts in successfully adopting and deploying big data and providing strategies for organisations to improve their complexity tolerance and close the "Deployment Gap".

5.3 Discussion Pertaining to Technological Factors

Technological factors refer to the characteristics and capabilities of the technology itself that can influence the adoption process (Chen et al., 2015b).

This section discusses and reviews the findings from factors such as relative advantage, complexity, compatibility, trialability and data quality against the literature.

5.3.1 Relative Advantage

Proposition 4: Relative advantage influences the BDA adoption process.

According to Fichman and Kemerer (1993), when a new technology surpasses the previous one in terms of both cost and functionality, it is deemed to possess a relative advantage. The relative advantage, according to the majority of the participants, had an influence on the adoption processes of BDA within organisations due to its reach functionality. This observation corresponds with the finding made by Walker and Brown (2019) that BDA provides significant benefits over traditional BI systems, which utilise technologies such as data warehouses and BI reporting tools to deliver information for decision-making.

The findings also showed that many of the organisation's legacy systems have limitations and that their traditional BI platforms do not have the functionality to process a variety of data types (i.e., unstructured), and thus, adopting new technologies that have fewer limitations allows them to progress and operate with less effort. Participants in a similar study conducted by Walker and Brown (2019) noted that BDA provides the ability to mine across structured and unstructured data and add real-time triggers for deeper insights, which is limited to traditional BI systems.

Furthermore, relative advantage has saved costs for organisations by allowing them to leverage existing systems and platforms while adding and expanding their capacity through the efforts of understanding what the new systems bring to the table. If the cost of adoption is perceived as too high, this can create barriers to adoption and limit the potential benefits of big data adoption (Sun et al., 2018). These findings are aligned with the perceived value of relative advantage.

5.3.2 Complexity

Proposition 5: Complexity influences the BDA adoption process.

Complexity is defined as the perceived degree of difficulty and understanding in providing security mechanisms for BDS (Salleh & Janczewski, 2016). Higher (perceived) complexity is normally associated with higher levels of uncertainty in relation to the successful adoption of new technology (Grover, 1993). Similarly, to the original study, this research is based upon the findings showing that complexity negatively impacted the BDA adoption process.

The findings showed that there were various thoughts regarding the influence of complexity in the BDA adoption process; however, for most participants, the complexities did influence the adoption process. This was because the new data format (i.e., unstructured) being ingested required new skills and capacities that may not have been readily available within the organisation, thus, requiring organisations to find those skills either by developing the skills of people within the organisation through training or by hiring new talent altogether. Sun et al. (2018) posit that organisations may need to invest in training and development programs to ensure that their employees have the necessary technical expertise to implement and use big data effectively, or they may need to hire new employees with the necessary skills and expertise.

Additionally, organisations may need to work closely with vendors and consultants to ensure they implement and use big data effectively. Sun et al. (2018) echoed the same sentiment by stating that organisations need to ensure they have the necessary technical expertise and resources to implement and use big data effectively and understand the potential risks and benefits of big data adoption.

Some participants shared practical examples, and one of them was when one of the organisations thought that they were experiencing a business problem, only to find out during their investigations that they were experiencing a big data problem. It took them time to research and find a solution to handle and process the amount of data they were handling. Because of their stage during their adoption process, dealing with this complexity was not necessarily seamless for them. Walker and Brown (2019) stated that an array of technologies have rapidly evolved to address the technical challenges stemming from big data and its characteristics. These technologies include data lakes, stream analytics, mobile analytics, and so on. In their research, they went on to state that adopting these technologies can add complexity to the deployment of BDA systems.

However, for some organisations, this was not the case as they felt that the complexities in BDA did not affect them due to not needing speed and veracity and having the capacity to deal with them; thus, BDA complexities are not influencing the adoption or its intention.

5.3.3 Compatibility

Proposition 6: Compatibility influences the BDA adoption process.

As Nedev (2014) stated, compatibility refers to the level at which a new technology integrates harmoniously with an organisation's existing needs, practices, past experiences, and values. In the context of big data, compatibility refers to the degree to which big data is perceived as consistent with the existing IT infrastructure and organisational needs (Sun et al., 2018).

The findings highlighted mixed emotions and a variety of opinions when it came to compatibility and its influence on the adoption process. However, one theme was prevalent among participants: integrating the new and the old to achieve organisational goals and targets.

The findings showed that older organisations were seen to experience more complications and complexities when undergoing integration within BDA adoption, as older technologies were difficult to integrate with, and the organisation's history also played an important role in this process. This observation corresponds with the view shared by Chen et al. (2015a) that an organisation's capabilities are influenced by its historical background and previous experiences, which are indicative of its values and operational methods. Suppose big data is not perceived as compatible with the existing IT infrastructure or organisational needs. In that case, this can create barriers to adoption and limit the potential benefits of big data adoption (Sun et al., 2018).

The newer and younger organisations, on the other hand, were seen to experience fewer complications and complexities when integrating, particularly because they did not have legacy systems and long histories to integrate into their adoption process. This notion corresponds with the observation made by Sun et al. (2018) that organisations need to ensure that big data is compatible with their existing IT infrastructure and systems in order to integrate it effectively and realise the potential benefits of big data adoption.

It was also evident that most organisations centred themselves around a certain niche of services they provide, and this positioning influences the technology and systems they choose to use or require. Thus, most of these organisations have not found compatibility as an issue or influence in their adoption process either because they have positioned their organisations for them or because these new systems have been prepared for or planned for within their growth plans. This view is further supported by the observation made by Sun et al. (2018) that organisations need to ensure that big data is compatible with their organisational needs and goals and that it aligns with their overall business strategy.

5.3.4 Trialability

Proposition 7: Trialability influences the BDA adoption process.

The findings showed that the ability to test and trial systems had to some extent, an influence on BDA adoption; however, not to a very large extent. This is because organisations can actively learn and gain valuable insights through practical experimentation and hands-on experiences. According to Ahmad et al.

(2016), the trialability of innovations plays a crucial role in reducing uncertainty surrounding their adoption.

Other participants stated that they adopt the use case test approach to trial and error with the technology to be implemented by trying to address specific business problems. A study conducted by Walker and Brown (2019) found that trialling BDA allows organisations to understand the challenges that could be experienced during implementation, and the learnings from the trial could prevent organisations from making similar mistakes in production. This allows them to learn more about it and what it can do and gives them the confidence to implement and support other organisational departments in utilising the product, especially when looking at technology maintenance. Walker and Brown (2019) affirmed that this approach could help to reduce the risk associated with BDA adoption and increase the likelihood of success.

Furthermore, findings showed that testing and trailing of the products enable organisations to understand how safe the program or system is for their customer data and company data, with the added opportunity to assess the data quality brought about by the BDA system implemented. Sun et al. (2018) posited that if the data is of poor quality, this can lead to a lack of trust in the data and the analysis, which can limit the potential benefits of big data adoption.

Interestingly, a participant highlighted that most organisations would test a new product mainly because they are already shopping for it. This is usually because their current product was insufficient or expensive; hence, trialability was not a huge factor when it came to adoption, although it was a factor.

5.3.5 Data Quality

Proposition 8: Data quality refers to the relevance, timeliness, reliability, and accuracy of the outputs.

In the realm of big data analytics, the collection and integration of data from multiple sources are fundamental. It is important to note that the quality of the data directly impacts the decision-making process. Numerous studies (Fredriksson, 2015; Malaka & Brown, 2015; Zhu et al., 2016) highlight that relevant, timely, reliable, and accurate data positively influence decision-making. In other words, the higher the quality of the data in terms of these attributes, the greater its impact on the decision-making process

Research findings also showed that data quality was consistently important, whether during BDA or traditional BI system implementations, as this was the requirement in financial organisations. Sun et al. (2018) posited that organisations need to ensure that the data they collect and use for analysis is of high quality in order to make informed decisions and gain insights into their operations and customers.

However, there were discrepancies in the importance of data quality depending on the case that was being solved; this meant that some cases had critical data that did not allow for bad data at all, and there were cases where there would be a percentage for exceptionality regarding data quality, called a tolerance scoring, and this allows so for some imperfections in the data. However, data cleaning was an important step in making sure that the quality of data was good, whether it was a BDA or BI system, because the data was eventually used to build models and make important decisions regarding organisations and their financial health.

5.4 Discussion Pertaining to Organisational Factors

Organisational factors encompass an organisation’s internal attributes that can influence the adoption of BDA. In this research, the findings from factors such as Top management support, Human resource expertise, Business and information technology alignment, and Organisation size are unpacked and reviewed against the literature.

5.4.1 Top Management Support

Proposition 9: Top management support influences the BDA adoption process.

This proposition aimed to ascertain whether top management support does influence the adoption process for BDA. The findings from this research show that the support of top management had a major influence on the BDA adoption process, as top management with any organisation were the main decision-makers. According to Mungree et al. (2013), top management has a significant impact on addressing organizational issues related to Business Intelligence and Analytics (BI&A) implementation. They have the ability to provide the necessary resources, whether financial or human, and can also prioritize, support, and endorse the use of BI&A within organizations. Specifically, top managers' decision-making culture and ability to support the adoption of big data can influence the organisation's readiness to adopt big data (Sun et al., 20218).

Top management's buy-in into BDA within an organisation usually meant that the entire organisation would buy in. This notion is further supported by Walker and Brown (2019), who stated that top management support is crucial for successful BDA adoption because it ensures that the organisation's culture, norms, and values are aligned with the technology.

Top management involvement within organisations enables teams to involve users in their research to understand how the BDA will fit within their organisation. If it succeeds as intended, this step is usually unachievable without the buy-in and or support of top management, executives, and the organisation's board.

These findings support the notion by Ahmad et al. (2016), Chen et al. (2015a), Hung et al. (2016), Nedev (2014), and Salleh and Janczewski (2016) that if senior management maintains a positive perception regarding the potential advantages of an IT system, they will proactively undertake actions to promote its adoption and implementation.

Moreover, the findings showed that top management was responsible for setting up KPIs and resource allocation, including finances; hence their buy-in and support were crucial in organisations. Some participants also highlighted how difficult it would be to implement any strategy or innovation in an organisation without their support (using the words "it would not be practical"). This further highlighted the importance of top management in the adoption of BDA or any other new systems. This finding is further supported by the notion that top management can help to create an information-sharing culture within the organisation, which can facilitate the adoption of big data (Sun et al. 2018).

Other participants even said it was a rule for innovation and that these changes come from the top. That way, there would be support for the changes brought about by the implementation. In other organisations, analytical data roles were put in place to sit at top management levels so that they could influence discussions, especially ones centred around BDA adoption.

This finding is supported by the view from Chen et al. (2015a), which states that top management plays a crucial role in driving organisational change by actively championing and promoting the implementation of the system. In doing so, they act as agents of change, facilitating the transformation of the organisation's culture, norms, and values (Chen et al. 2015a).

5.4.2 Human Resource Expertise

Proposition 10: Human resource expertise influences the BDA adoption process.

After establishing top management support, next was making sure that the organisation had the necessary skills and capacity to drive the new venture. The findings from the primary research showed that the availability of human resource skills did influence the adoption of BDA as not every manager or leader was susceptible to change or had the necessary skills to drive adoption. If this was the case at leadership positions, it usually did affect the sub-ordinates, who were then forced to move at the pace of their leader or manager regarding the adoption. This observation is further supported by an observation made by Walker and Brown (2019), which suggested that organisations with more human resource expertise are more likely to adopt BDA successfully. This is because BDA requires specialised skills and knowledge, such as data engineering and data science, which may not be readily available within the organisation (Walker & Brown, 2019).

Other participants further explained the importance of having what they called doers. These were people who had the needed skills for the adoption process, which would then pioneer the skills used within the organisation and teach or share these skills with the rest of the team and, thus, the rest of the organisation. This notion is further supported by the observation made by Lautenbach et al (2017) that organizations need to ensure that they have the necessary talent and expertise to derive value from their data assets. This may involve investing in training and development programs, partnering with external providers, or adopting new talent management strategies to attract and retain skilled professionals.

These people (the doers) were important to the adoption process; without them, the strategies in place were just a picture and would not be realised. This finding is further affirmed by Sun et al. (2018) that organisations need to have employees who possess the necessary technical skills, such as data analysis, data management, and data visualisation, to work with big data.

The prominent challenge identified in a study examining the failures of implementing BDA was the significant lack of skills, as emphasised by Fredriksson (2015). This underscores the critical importance of acquiring the requisite expertise for successful BDA implementation. Another different opinion was that participants felt that there were skills within the industry to handle BDA. However, there was no guidance and support for those skills to grow and further support the industry itself, which affected BDA's adoption process and implementation. This could be attributed to the lack of a clear career path and attractive compensation for the right personnel. This means that organisations' ability to attract and retain skilled personnel is also important for the adoption of BDA. Sun et al. (2018) stated that organisations need to have competitive compensation packages and a positive work environment to attract and retain skilled personnel who can work with big data.

In the broader context, the significance of human resources expertise cannot be overstated when it comes to the adoption of big data in organisations. To effectively embrace and leverage big data, organisations must prioritise investments in developing and retaining skilled personnel. By nurturing a talented workforce, organisations can enhance their capabilities and successfully navigate the complexities associated with adopting and utilising big data.

5.4.3 Business and Information Technology Alignment

Proposition 11: Business and IT alignment influence the BDA adoption process.

The concept of business and information technology alignment refers to the extent to which an organisation's business and IT strategies are harmoniously integrated (Walker & Brown, 2019). The findings of this research showed that the alignment of business and IT was important not only for BDA adoption but also for the general functioning of the organisation, as IT played a support role for the organisation.

However, there seemed to be some complexities when it comes to communication between IT and business. Participants who were in IT departments felt that businesses tended to not fully engage in the process and somehow just iterated what they wanted or needed but did not fully participate in the creation process, which then caused missed communication, often resulting in businesses not feeling heard by the IT department. It was obvious that the misalignment of IT and business often resulted in chaos and dysfunction, which often led to unproductiveness.

In this regard, Chen et al. (2015b) proposed that organisations should establish a Centre of Excellence which can help organisations effectively manage the complexity associated with big data adoption and deployment. One of the key functions of a centre of excellence in the context of BDA is collaboration and support, which is focused on Facilitating collaboration and knowledge sharing among different teams and departments within the organisation, providing support and guidance throughout the adoption and deployment process (Chen et al. l, 2015b).

Other participants stated that their organisations were able to align the IT and business by creating a channel or a bridge between business and IT, allowing them to properly communicate ideas up until the business goals are achieved. The manner of communication was also important because the way business understands concepts could be different from how IT understands business. This observation was supported by the views of Sun et al. (2018), who stated that the integration of business and IT is also important for the adoption of big data. Organisations need to have effective communication and collaboration between business and IT teams to ensure that big data initiatives align with the organisation's overall goals and strategy (Sun et al., 2018).

Continuous research in information technology management has consistently highlighted the importance of aligning business objectives with information technology, as Kappelman et al. (2014) emphasised. This alignment becomes particularly crucial in the context of BDA, where Chen et al. (2015b) asserted that it significantly influences the adoption and successful implementation of BDA. Therefore, establishing a cohesive relationship between business goals and information technology is essential to maximise the effectiveness and benefits derived from BDA.

5.4.4 Organisation Size

Proposition 12: Organisation size influences the BDA adoption process.

When participants were asked if they thought organisational size influenced the adoption of the BDA within their organisation, it was not surprising to discover that the organisational size was inversely proportional to the adoption process. When it comes to larger organisations, specific obstacles require careful consideration and resolution. Addressing these factors becomes crucial to ensure a smooth and successful implementation of changes within the organisation, allowing for effective adaptation and progress.

While the literature showed that larger firms might have more capital and human resources to ensure that technology can be well adopted (Rosli et al., 2012), the findings from the research, on the other hand, revealed that the bigger the organisation, the more complex it was for the organisation to implement or adopt BDA. The findings of this is study contradicts with the findings from Pries and Dunnigan (2015) who noted that larger organizations that generate or have been dealing with large data volumes from different sources for decades are more likely to be early movers.

Due to that, there were a lot of factors to consider, such as the number of ideas, leadership styles and teams to integrate with the adoption. While factors from the research findings may differ from the ones from the literature, which are the integration of knowledge from different departments, objective operational adjustments and data amendments (Sun et al., 2018), the common theme is that the bigger the organisation, the more complex it was to adopt and integrate new systems, for reasons such as organisational history or legacy as well as the increased number of teams or functioning levels to integrate while undergoing adoption.

On the other hand, the research findings showed that the challenges experienced by small organisations were different from those of large organisations as they (the smaller organisations) did not have legacy systems to integrate into their adoption process. One major challenge cited by participants from smaller organisations was the issue of finance, which translated to being unable to finance mistakes in BDA adoption, which meant that they had to make sure it would work for them before implementing, thus slowing down their adoption process as much research and consultation had to take place before investment could be made. Walker and Brown (2018) suggested that smaller businesses may have a longer payback period for BDA adoption due to the high cost of implementation.

5.5 Environmental Factors

Environmental factors refer to the external factors outside of the organisation that can impact the adoption of big data (Sun et al., 2018). This research covers environmental factors such as Competitive pressure, Data privacy, Vendor support, and Information technology fashion.

5.5.1 Competitive Pressure

Proposition 14: Competitive pressure influences an organisation's complexity tolerance.

The effects of competitive pressure influence on an organisation's ability to tolerate complexities were noted as a very important aspect for managers to deal with in the BDA adoption process. One participant highlighted how important it was for managers to manage these complexities effectively. Thus, the competitive pressure added to organisational complexities, with managers required to handle this added complexity. Organisations that feel pressure to adopt big data quickly may be more likely to overlook the complexities and risks associated with big data adoption (Sun et al., 2018).

However, most participants did not feel that competitive pressure influenced their organisation's ability to deal with or cope with complexity due to the rigorous processes they undertook before adopting any system that the competition used. Although the competition did apply pressure in terms of organisations wanting to remain at the top of their game and serve their customers in the most efficient ways, most of the organisations had regulations to adhere to, especially because they operate in the financial sector. This finding is aligned with the observation made by Sun et al. (2018) that Organisations that face strong competition may be more willing to tolerate the complexities of big data adoption if they believe that it will give them a competitive advantage. When an organisation faces competitive pressure, it may be more willing to tolerate the complexity of the BDA adoption process in order to gain a competitive advantage (Walker & Brown, 2019).

The research findings showed that regulatory red tape forced organisations to think before applying any new methods, to try and find the best fit for them and their customers in changing times. Sun et al. (2018) posited that competitive pressure can create a culture of risk-taking within the organisation, which can lead to poor decision-making and implementation. This view from literature combined with research findings suggests that regulatory controls (red tape) should be seen as a positive for the organisation and its customers.

Some organisations did not find competitive pressure to inhibit their ability to tolerate complexities because they were relationship-based organisations. Their clients were not necessarily with them because they had the latest tech or followed the latest trends within the industry. However, their clients were with them because they had a trustworthy reputation and relationships throughout the years.

Other organisations felt that they had a better competitive edge than smaller organisations that do not have the same financial capacity to absorb the mistakes that come with adoption. Because of this advantage, the competitive pressure does not influence their ability to tolerate complexities because their organisation already has a large capacity for complexities. On the contrary, some organisations, although young and smaller than experienced and larger organisations, felt they still had a competitive advantage because they were bringing new solutions into the industry that were different from traditional organisations.

Proposition 13: Competitive pressure influences the BDA adoption process.

Competitive pressure refers to the external force exerted by competitors, compelling organisations to continuously stay updated and embrace new information about customers. This pressure pushes organisations to remain competitive in the market by adapting to changing customer needs and preferences. Sun et al. (2018) posited that organisations that are early adopters of big data may be able to establish themselves as leaders in their industry, which can help them attract customers and talent.

Much like the effect of competitive pressure on complexity, competitive pressure did not have much of an influence on the adoption of BDA, as many of the participants felt that competitive pressure was not necessarily directly from their competitors but was mostly from their customers who wanted certain services, or from potential customers they possibly could service because there was an opportunity to gain those customers or expand to into that market. This finding is supported by the observation made by Walker and Brown (2019) that stakeholders such as customers, suppliers, and competitors all contribute to competitive pressure on organisations. By analysing customer data, organisations can gain insights into customer behaviour and preferences, which can help them personalise their products and services and improve the overall customer experience (Sun et al., 2018).

Most participants acknowledge that the positive aspect of competitive pressure is that it kept organisations on their toes and enabled them to keep up to date with what was occurring within their industry and what the future of their industry was looking like. The research conducted by Masrek et al. (2009) highlights that organisations operating within competitive environments are more prone to strategically adopt and effectively utilise information systems (IS). The competitive landscape serves as a catalyst, driving these organisations to recognise the value of IS and leverage them as strategic assets for gaining a competitive advantage. The same conclusion is drawn in the context of BDA adoption.

5.5.2 Data Privacy Concerns

Proposition 15: Data privacy concerns influence the BDA adoption process.

A very important aspect of data handling was data privacy, significantly when it came to financial institutions, which dealt with sensitive information regarding people's personal finance and sensitive information regarding other organisations' financial health. As mentioned earlier, this data was highly regulated, and thus there was a lot of protocol surrounding the data in these organisations. According to the findings of Richards and King (2014), concerns surrounding privacy, confidentiality, and identity arise when dealing with big data. Zanten et al (2012) affirmed that since many organizations store Big Data in the cloud environment, the security of their data is a critical issue and is an essential antecedent for Big Data adoption.

The participants generally agreed that there was a need for these regulations but still felt that the regulations did slow down the adoption processes as, as mentioned, they had to make sure they took long processes to ensure that their actions were not only ethical but with regulation guidelines when using the data. Sun et al. (2018) posited that if the government imposes strict regulations or restrictions on the use of big data, this can limit the potential benefits of big data adoption and create barriers to entry for organisations.

However, the difference of opinion came when some participants felt that data privacy concerns were not unique to just BDA. Other participants argued that the POPI Act made things a little more rigid. Thus, it took longer to implement and adopt BDA due to these added restrictions and complexities brought by BDA and other regulations such as the POPI Act. This finding suggests that the regulators ought to be clear about rules, regulations, and restrictions for the use of BDA.

This finding is aligned with the observation made by Sun et al. (2018) that if the government does not provide clear guidelines or regulations for the use of big data, this can create uncertainty and confusion for organisations and make it difficult for them to understand the potential risks and benefits of big data adoption. According to a report by Forbes Insights (2015), organizations need to exercise caution regarding the growing influx of data from diverse sources, as there is a potential rise in cybersecurity attacks and fraudulent activities.

These observations align with the original research findings, where data privacy was seen to have a negative effect on the adoption process (Walker & Brown, 2019). Although there is a growing body of literature discussing the privacy and security implications of big data, there is still a scarcity of empirical studies examining the adoption of big data by organisations and the associated security factors that may influence the intention to adopt (Ahmad Salleh et al., 2015; Kshetri, 2014).

The use of big data in the banking industry can pose some potential risks, such as data privacy and security concerns, regulatory compliance issues, and reputational risks. However, these risks can be mitigated through proper data governance, risk management, and compliance measures (Amakobe, 2015).

5.5.3 Vendor Support

Proposition 16: Vendor support influences the BDA adoption process.

There were various sentiments shared by participants when it came to the effects of vendor support on the BDA adoption process, with some feeling that vendors needed to understand the technologies and right solutions for their organisations, as their organisations leaned heavily on vendor support. Walker and Brown (2019) posit that the right vendor should have experience in putting down a BDA and driving adoption with the business.

This was because the vendors and organisations were in end-to-end agreements where the vendors supported the organisation with implementation, maintenance, upgrades, advisory and engagement. Thus, if they did not have adequate vendor support, they would find it very difficult to implement and adopt BDA into their organisation. This sentiment is supported by Walker and Brown (2019), who suggested that using the right vendor is critical for successful BDA adoption. They went on to state that the right vendor should have experience in putting down a BDA environment and driving adoption with the business.

For other organisations, it depended on the particular software they were getting from their vendors. It was highlighted that plug-and-play software or subscription type of software was less affected by vendor support, but that most other types of software were affected by vendor support, and if there was not adequate support for the organisations from those vendors, then they would experience difficulties with the adoption of BDA. This finding is supported by an assertion from Lutfi et al. (2022), which stated that vendors of big data could provide technical support for operators to improve their usage capabilities and address and resolve complex activities carried out through the system. In addition, vendors need to provide sufficient technical training and support to promote big data adoption. Lautenbach et al (2017) also affirmed that organisations need to consider the technological context when implementing business intelligence and analytics practices and tools, and that vendor support is an important factor to consider in this regard.

Finally, some participants felt that although vendor support was important and played an important role, it did not have a big influence but would affect the rate at which adoption occurred, slowing it down but not inhibiting it. This finding contrasts with different views from the literature. For example, Walker and Brown (2019) stated that vendor support could play a critical role in the adoption process of BDA, particularly for organisations that do not have the necessary in-house expertise.

5.5.4 Information Technology Fashion

Proposition 17: Information technology fashion influences the BDA adoption process.

Based on the findings of the research, IT fashion did not play a significant role in the BDA adoption process because although new technology came into the market and it had a big impact on the market, organisations had to first evaluate if the technology would work for their business goals or their organisation entirely.

Furthermore, organisations had to prepare for the technology in terms of skills and organisational culture. Thus, they would not buy into it if they were not ready to implement or adopt new trendy technology from a business perspective. Walker and Brown (2019) suggested that organisations need to have the necessary in-house expertise to implement BDA successfully. This includes data scientists, engineers, and other IT professionals with experience working with big data technologies.

These findings corresponded with literature observations that organisations need to be careful when adopting big data simply because it is fashionable or trendy. They need to ensure that they are making informed decisions and implementing big data effectively to realise the potential benefits (Sun et al., 2018).

The findings also showed that regulations partly contributed to the organisation's hesitation in adopting new technology because, as mentioned earlier, organisations had to be fully compliant with regulatory requirements before implementing or adopting new technology, which calls for the necessity to prepare before they implement. Moreover, the financial implications of jumping into trends were one thing organisations had to consider, not neglecting that some of these new technologies offered good functionalities that could be useful to the organisation. Organisations need to be aware of the potential risks associated with adopting big data, such as privacy and security concerns and ensure that they are addressing these risks effectively (Sun et al., 2018).

Proposition 18: Information technology fashion influences an organisation's complexity tolerance for BDA.

It was expected that IT fashion influence did not influence an organisation's ability to tolerate complexity because, as previously discussed. Regulatory considerations, on the other hand, were a contributing factor. Also, it was important for most organisations to integrate the new technology into their daily function and/or future goals and prospects to maintain their business legacy and objectives.

By evaluating if the organisation has the necessary skills to implement the new technology, the following questions emerged: does the new tech solve the specific business problem? Will it have the desired impact? Do they have the capacity to handle the tech, and do the relevant resources have the capacity? These are some of the questions that organisations must ask themselves before integrating the fashion trends in IT into their organisation. Zhu et al (2006) stated that organisations that have strong supportive data-related infrastructures are better positioned to extensively use BI&A. Chen et al. (2015b) described these as organisational capabilities which entail IT infrastructure, leadership, and workforce skills. These capabilities are important for absorbing paradigm shifts and tolerating complexity, which is key factors in successfully deploying big data (Chen et al., 2015b).

Although not much of an influence, organisations still had to be aware of IT fashion trends and their impact on their industry. Interestingly some organisations found IT fashion to influence their ability to tolerate complexities because some of the solutions made their processes simpler and easier to implement and handle. Although this influence was not great, it was not negligible. Wang (2006) found that companies associated with IT fashions did not have higher performance, but they had better reputation and higher executive compensation in the near term. Companies investing in fashionable IT had lower performance in a short term but improved their performance later. Chen et al. (2015b) emphasised the importance of evaluating technology objectively and being aware of the potential influence of trends or fashion on adoption decisions.

5.5.5 Regulatory Requirements

Proposition 19: Regulatory requirements influence the BDA adoption process.

The role of the regulatory environment is a major factor in the implementation process of BDA in organisations. This was mainly because financial services are a highly regulated sector both in South Africa and worldwide. The findings showed that there were many requirements surrounding data security, data privacy and data quality, and the ability to pull data for live testing that organisations had to manoeuvre around during adopting BDA. A study by Lutfi et al. (2022) highlighted that security concerns are a significant barrier to adopting big data analytics, particularly in relation to data-related innovation adoption.

However, most organisations' solutions were built around these regulation requirements, making it easier for them to handle and implement BDA. The type of data influenced the level of regulatory requirements an organisation would have to adhere to, and it was found that big data had a huge number of regulatory requirements; thus, organisations would have to systematically position themselves to adhere to the requirements before they could fully use BDA in their organisation. Walker and Brown (2019) confirmed that ensuring compliance with regulatory privacy requirements is far more complex when dealing with predominantly unstructured data, which is the foundation of BDA.

Due to data privacy concerns, the regulatory requirements have become some of the most important aspects of adoption organisations would have to consider, as failure to fulfil regulatory requirements meant that they could not implement BDA in their organisation. Thus, the influence of regulatory environments is that they limit and could inhibit adoption, especially if they are not adhered to. Lautenbach et al (2017) noted that the pressure to comply with regulatory requirements was thought to have a positive influence on the Business Intelligence and Analytics usage extent to satisfy these reporting requirements.

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

This chapter provides a conclusion to the study by addressing the research objectives outlined in Chapter 1. Additionally, the chapter evaluates the limitations of the study and put forward suggestions for future research.

The research study had the following three objectives:

- to understand factors that influence Big Data Analytics adoption in the South African Financial Service Industry,
- to understand how these factors influence investment decision-making in Big Data Analytics, and
- to understand how the value of Big Data Analytics adoption is measured post-implementation.

6.2 Conclusions

The conclusions related to the three research objectives are presented in the sections below.

6.2.1 Conclusion related to research objective 1

This objective sought to determine what factors contribute to the adoption of BDA in the South African financial industry. The findings of the study showed that most financial organisations are at different levels of maturity when it comes to BDA adoption. In some instances, different departments within the same organisation were at different levels of maturity. This could be attributed to factors such as alignment between business unit leaders and IT as a result of the alignment of strategies or clear communication between both departments, human resource expertise as some departments might have the necessary skills required to adopt

BDA and compatibility where systems from that particular department are compatible with the BDA platform that is being adopted.

Top management support was identified as the major influence for BDA adoption because it establishes key performance indicators (KPI) and allocates necessary resources such as finances. Stricter regulations meant that financial institutions could not just adopt any new trendy technology without conducting any due diligence, which resulted in the slow uptake of that new technology. While this might have a negative impact in hindsight, financial institutions prefer to adopt the tried and tested technologies with good vendor support and can be compatible with existing platforms and systems. Furthermore, regulations such as the POPI Act have posed some restrictions regarding how financial institutions make use of their customers' data.

Financial organisations appear to be missing a skills development and retention strategy for relevant data analytics practitioners. Therefore, financial organisations must establish clear career development roadmaps to ensure that they develop, retain and grow their capability. This study also showed that the size of the organisation does not influence the adoption of BDA. However, it could inhibit adoption, especially for larger financial organisations, due to lengthy processes, red tape and a silo mentality. Smaller organisations, on the other hand, most of whom are born digital, demonstrated agility and nimbleness to adopt BDA.

Most financial institutions are plagued by legacy infrastructure incompatible with the latest BDA platforms. This leads to complexities around adoption and has the potential to derail the adoption process. While trialability was identified as an important factor, the approach that was pointed out as beneficial was the proof of concept (POC) method, which enabled organisations to test the platform by solving a specific business problem before adopting it. The findings suggest that partnerships with technology vendors helped to accelerate the adoption of BDA. These strategic partnerships allowed financial service institutions to access external expertise to facilitate faster implementation and improved outcomes.

To summarise, the findings of this study offer empirical support for the notion that organizations that possess a strong ability to handle complexity are more inclined to swiftly progress from the intention to adopt Big Data Analytics (BDA) to its successful implementation, thereby effectively minimizing the gap in deployment. By recognising the significance of complexity tolerance, organisations can better position themselves to embrace BDA and harness its transformative potential.

The next objective discusses how these factors influence investment decision-making in BDA adoption.

6.2.2 Conclusion related to research objective 2

The second research objective was to understand how these factors influence investment decision-making in Big Data Analytics.

While none of the factors could be individually linked to investment decision-making, this study found that a combination of factors such as top management support, relative advantage, trialability, human resource expertise (in some instances, the availability of the doers), regulatory environment and vendor support did influence investment decision-making collectively for most of the organisations. Also, the push from the regulators and the need by financial organisations to improve customer experience led to an acceleration of BDA adoption, which ultimately led to investment decisions being made to meet these objectives.

Lastly, the predefined KPIs for financial institutions, such as Cost to Income, Net Interest Revenue, Non-interest Income, and Credit Loss Ratio, cannot be overlooked as they can also influence the decision by businesses to invest in BDA. It is, therefore, advisable that the leaders of the BDA initiative ensure that their program strategies are aligned with these traditional KPIs to ensure that the outcomes of BDA address the right metrics and that the immediate needs of relevant business stakeholders are addressed accordingly. This could lead to more investment (such as budget allocation, resource allocation, and top management support) being allocated to BDA programs.

6.2.3 Conclusion related to research objective 3

While the literature stated that the tangible benefits that an organisation can derive through the use of Business Intelligence and Analytics are hard to quantity (Watson & Wixom, 2007), this study found that all organisations who participated in this research have implemented BDA either at enterprise-wide or business unit levels, and in so doing, they have developed measures such as customer-centric metrics to measure improvements in customer satisfaction, retention and attrition rates and engagement levels. Other measures, such as risk management enhancements, are used to assess improvements in risk management processes, such as fraud detection and prevention, regulatory compliance, and early identification of potential financial risks.

On the revenue generation side, the findings showed that some organisations had leveraged BDA to expand their traditional product and value offerings to platform business models offering better customer service and higher revenue margins. Measures such as cross-selling or upselling effectiveness have been adopted.

6.3 Recommendations

While there might be many other methods of adopting BDA, the recommendations in this study are based on the input from participants and the analysis conducted in this paper. Below are some of the recommendations that organisations within the financial services sector can adopt to ensure the successful adoption of BDA:

- **Develop a comprehensive data strategy**: Create a well-defined data strategy that aligns with your organisation's business goals and objectives. This strategy should outline how BDA will be integrated into your existing operations and the key metrics for success.
- **Prioritise data security and privacy**: As data is a critical asset in the financial services sector, it is essential to prioritise data security and privacy. Implement robust security measures and comply with relevant data protection regulations to maintain the confidentiality and integrity of customer information.
- **Establish a scalable infrastructure**: Build a scalable infrastructure that can handle the volume, velocity, and variety of data generated in the financial services sector. Consider cloud-based solutions for storage and processing capabilities, ensuring they meet the industry's regulatory requirements.
- **Foster cross-functional collaboration**: Encourage collaboration between IT teams, data scientists, business analysts, and other stakeholders to ensure a comprehensive understanding of the organisation's data needs. This collaboration will facilitate the identification of valuable insights and the development of practical analytics solutions.
- **Invest in data quality management**: Emphasise data quality management practices to ensure accurate and reliable data. Implement data cleansing, standardisation, and validation processes to enhance the integrity of the analytics outcomes and decision-making processes.
- **Leverage advanced analytics techniques**: Explore advanced analytics techniques, such as machine learning algorithms and predictive modelling, to derive meaningful insights from large datasets. These techniques can assist in areas like risk assessment, fraud detection, customer segmentation, and personalised financial recommendations.
- **Develop talent and skills**: Invest in training programs and talent acquisition to build a skilled team capable of handling BDA in financial services. Develop a multidisciplinary team with expertise in data science,

statistics, domain knowledge, and business acumen to extract maximum value from your data assets.

- **Ensure regulatory compliance**: Stay current with the evolving regulatory landscape and comply with industry-specific regulations, such as the Financial Sector Regulation Act (FSRA) and the POPIA. This includes managing customer consent, data storage, and data transfer in accordance with the applicable laws.
- **Embrace a culture of innovation**: Foster a culture that encourages innovation and experimentation with data-driven approaches. Encourage employees to explore new ideas, share insights, and leverage data analytics to drive continuous improvement across different business functions.
- **Continuously evaluate and optimise**: Regularly evaluate the impact and effectiveness of your BDA initiatives. Monitor key performance indicators (KPIs) aligned with your business objectives and make adjustments as needed to optimise the value derived from your analytics investments.

6.4 Study Limitations

Nine out of 10 interviews were conducted online, and while this might have benefited from a logistical cost perspective, challenges were encountered due to load shedding. For that reason, two interviews had to be rescheduled. Another limitation was that the researcher was unable to conduct the interview at the initial time set out with participants due to certain administrative processes not being dealt with in time by the school. This resulted in cancellations by two original participants from the study, which meant that the researcher had to extend the invitation to two new participants. Both limitations had a negative impact on the time allocated for data analysis.

In certain cases, the extended length of the research instrument had an adverse effect on the data quality as certain participants appeared reluctant to elaborate on or offer extensive input regarding their responses. This potentially constrained the depth of insights obtained from the analysis, consequently impacting the overall richness of the results.

6.5 Areas for Future Research

With the emergence of new technology, such as Generative Artificial Intelligence which promises to revolutionise the way information is consumed, BDA will continue to evolve at a rapid rate. Some of the factors (such as data privacy and regulatory concerns) and challenges uncovered in this study will influence the adoption of BDA. For this reason, the following future research topics are suggested:

- **Adoption challenges**: Explore the challenges faced by financial service institutions in South Africa during adoption and implementation of BDA. Investigate factors such as organisational resistance, cultural barriers, skill gaps, and data quality issues that may hinder successful adoption.
- **Ethical considerations**: Investigate the ethical implications of BDA in the financial services sector in South Africa. Examine topics such as data privacy, consent management, algorithmic bias, and fairness in decision-making to ensure responsible and ethical use of customer data.
- **Data governance and security**: Investigate the strategies and frameworks for effective data governance and security in the context of BDA in financial services. Explore approaches to ensure data quality, protection against cyber threats, secure data sharing, and compliance with data regulations.
- **Regulatory landscape**: Study the impact of South African regulations, such as the POPIA and FSRA, on implementing and operating BDA in the financial services industry. Analyse the compliance requirements, potential bottlenecks, and the effectiveness of regulatory frameworks in addressing data protection and privacy concerns.
- **Real-time analytics**: Explore the use of real-time BDA in financial service institutions in South Africa. Investigate the potential benefits, challenges,

and technological requirements for real-time analytics in areas such as fraud detection, trading, customer service, and risk management.

Overall, by undertaking research in these suggested areas, organisations within the South African financial services industry can unlock the full potential of Big Data Analytics, drive innovation, and stay competitive in a rapidly evolving landscape. The findings and insights gained from these research endeavours can shape the future of BDA adoption, implementation, and its impact on the industry, benefitting both organisations and their stakeholders.

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APPENDIX A – Participation Information Letter

Dear Participant,

My name is Siyabonga Mthethwa, and I am completing a Master of Management in Digital Business (MMDB) at Wits Business School. This research study is the final module of this program, and the title is "Factors Influencing the Adoption of big data analytics in the South African financial services industry". The objective of this study is to 1) explore factors influencing the adoption of big data analytics in the South African financial services industry, 2) understand how these factors influence investment decision-making for big data analytics projects, and 3) understand how the value of big data analytics is measured post-implementation.

Your expertise and knowledge within the financial service industry will contribute significantly; hence I would like to interview you for this research paper. If you agree to participate, I will email you a list of questions for you to think about ahead of our interview, and then we will schedule the interview for 60 minutes on a day and time that suits you. You're welcome to choose the preferred interview method between in-person (if you're based in Johannesburg) or virtual (i.e., MS Teams, Zoom, etc.). Please note that the interview will be recorded so that I can accurately report what you said. Furthermore, your participation is voluntary, and you are not forced to participate in this study. If you choose not to take part, you will not be affected in any way whatsoever. If you agree to participate, you may stop participating in the research at any time. If you do this, there will be no penalties, and you will NOT be prejudiced in ANY way. Any study records that identify you will be kept confidential as this is in accordance with the POPIA Act.

The records from your participation may be reviewed by people responsible for ensuring that research is done properly, including my academic supervisor. (All of these people are required to keep your identity confidential). All study records will be destroyed after the completion and marking of my thesis and the potential academic publication of the findings. I will refer to you by a code number in the thesis and any further publication. The results of this study will be presented anonymously, which means your identities will not be known to your employer or the readers of the final research document.

Should you agree to participate in this research, a consent form will be made available for you to sign before the start of the interview.

Yours Sincerely,

Siyabonga Mthethwa

Mobile: +27 73 072 7439

Email: smthethwa@gmail.com

APPENDIX B – Participant Agreement Form

I, ……… (participant's code), hereby give my informed consent to participate in the research study conducted by Siyabonga Mthethwa as part of his Master of Management in Digital Business (MMDB) at Wits Business School. I have not been coerced into participating in the study, but I have made an autonomous decision to participate.

The researcher has explained the research project to me and has assured me that my participation and responses to the interview questions will be kept private, anonymous and confidential.

I am aware that this research is conducted according to Wits Business School Policy on Research Ethics.

Participant's code: …

Signature: …………………………. Date: ____/____/ 2023

APPENDIX C – Interview Guide

Given that this will be a semi-structured interview, the exact questions posed during the interview may differ slightly but will convey the same meaning and understanding.

Initial Engagement:

- The researcher will call the participants to introduce the topic and the purpose of the research. During the call, participants will state if they consent to want to be part of the study.
- In the event they agree to participate, the researcher will set up an appointment at the time and location that suits the participant.
- An email explaining the purpose of the study and the participant's rights will be sent to the participant after agreeing to participate in the study.
- A meeting invite containing the meeting venue (Microsoft Teams or in-person) will be sent to the participant.

On the day of the interview:

- The research will inform participants that the meeting will be recorded, and the recording can be made available upon request.
- Furthermore, participants will be reminded of the confidentiality of the process, which entails concealing personal details (i.e., First Name and Last Name) and company names.
- Lastly, participants will be given an opportunity to ask questions before the interview commences.

The interview questions are outlined in Table 4.1.

Table 4.1: Consistency table for research objectives, propositions, data collection and data analysis

RO #	Research Objective	Prop #	Research Proposition	Data collection details/Interview Questions	Data analysis method
1	To understand factors that Influence Big Data Analytics Adoption in the South African Financial Service Industry	1	The organisation's complexity tolerance influences its ability to move from BDA intention to adopt actual deployment.	How does the organisation's complexity tolerance influence its ability to move from intention to adopt to actual deployment?	Thematic analysis
		2	The ability to absorb paradigm shifts influences the organisation's ability to move from BDA intention to adopt actual deployment.	What paradigm shifts has your company had to deal with during the BDA adoption process?	

RO #	Research Objective	Prop #	Research Proposition	Data collection details/Interview Questions	Data analysis method
		3	The extent of the paradigm shift influences an organisation's complexity tolerance for BDA.	How does the organisation's ability to cope with the paradigm shift influence its ability to move from intention to adopt to actual deployment?	
		4	Relative advantage influences the BDA adoption process.	How does the relative advantage of BDA influence the adoption process?	
		5	Complexity influences the BDA adoption process.	How do BDA complexities influence the decision and the adoption process?	
		6	Compatibility influences the BDA adoption process.	How does BDA compatibility influence the adoption process?	

RO #	Research Objective	Prop #	Research Proposition	Data collection details/Interview Questions	Data analysis method
		7	Trialability influences the BDA adoption process.	To what extent does having the ability to test new BDA technology influence your decision to adopt that technology?	
		8	Data quality refers to the relevance, timeliness, reliability, and accuracy of the outputs.	a) How important is Data Quality in the BDA when compared to traditional Business Intelligence (BI) systems?	
				b) How does data quality influence the BDA adoption process?	
		9	Top management support influences the BDA adoption process.	How does top management support influence the BDA adoption process?	

RO #	Research Objective	Prop #	Research Proposition	Data collection details/Interview Questions	Data analysis method
		10	Human resource expertise influences the BDA adoption process.	How does the level of human resource skills influence the BDA adoption process?	
		11	Business and IT alignment influence the BDA adoption process.	How does business and IT alignment influence the BDA adoption process?	
		12	Organisation size influences the BDA adoption process.	Does the size of your organisation have any influence on the adoption of BDA?	
		13	Competitive pressure influences the BDA adoption process.	How does competitive pressure influence the BDA adoption process?	

RO #	Research Objective	Prop #	Research Proposition	Data collection details/Interview Questions	Data analysis method
		14	Competitive pressure influences an organisation's complexity tolerance for BDA.	How does the effect of competitive pressure influence the organisation's ability to tolerate complexity?	
		15	Data privacy concerns influence the BDA adoption process.	How does data privacy influence the BDA adoption process?	
		16	Vendor support influences the BDA adoption process	How does the support from vendors influence the BDA adoption process?	
		17	Information technology fashion influences the BDA adoption process.	How does IT fashion influence the BDA adoption process?	
		18	Information technology fashion influences an organisation's complexity tolerance for BDA.	How does IT fashion influence the organisation's ability to tolerate complexity?	

RO #	Research Objective	Prop #	Research Proposition	Data collection details/Interview Questions	Data analysis method
		19	Regulatory requirements influence the BDA adoption process	How does the regulatory environment influence the BDA adoption process?	
2	To understand how these factors Influence Investment Decision-Making in Big Data Analytics	9	Top management support influences the BDA adoption process.	How does top management support influence the BDA adoption process?	Thematic analysis
		4	Relative advantage influences the BDA adoption process.	How does the relative advantage of BDA influence the adoption process?	
		7	Trialability influences the BDA adoption process.	To what extent does having the ability to test new BDA technology influence your decision to adopt that technology?	

RO #	Research Objective	Prop #	Research Proposition	Data collection details/Interview Questions	Data analysis method
		10	Human resource expertise influences the BDA adoption process.	How does the level of human resource skills influence the BDA adoption process?	
		19	Regulatory requirements influence the BDA adoption process	How does the regulatory environment influence the BDA adoption process?	
		16	Vendor support influences the BDA adoption process	How does the support from vendors influence the BDA adoption process?	
3	To understand how the value of Big Data Analytics	10	Human resource expertise influences the BDA adoption process.	How does the level of human resource skills influence the BDA adoption process?	Thematic analysis

RO #	Research Objective	Prop #	Research Proposition	Data collection details/Interview Questions	Data analysis method
	Adoption is measured post-Implementation	11	Business and IT alignment influence the BDA adoption process.	How does business and IT alignment influence the BDA adoption process?	
		19	Regulatory requirements influence the BDA adoption process	How does the regulatory environment influence the BDA adoption process?	

APPENDIX D – Ethics Clearance Approval

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number:	WBS/DB2500622/136

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	Factors influencing the adoption of big data analytics in the South African financial services industry
Investigator / Researcher	Mr Siyabonga Mthethwa
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed confidentiality.
Issue Date of Certificate	2023-01-18
Expiry date	Date of submission of the project / research report
Chairperson	Prof Anthony Stacey ☎ +27 11 717 3587 +27 82 880 4531 anthony.stacey@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

Date: