The adoption of big data analytics in South African financial institutions

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ABSTRACT

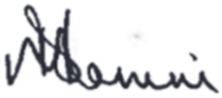
Financial institutions by nature of their operations handle a lot of information, to examine and extract value from the data they receive. However, with the increasing automation, the data they receive have change in volume and the speed at which it is generated necessitating them to learn new techniques to analyse this voluminous data also known as Big Data (BD). Much as this is so, there are still fewer frameworks and models that have been developed to guide the adoption of this big data analytics (BDA). More still, the available frameworks are not contextualised to perspectives of South African financial institutions. The main goal of the study was to develop a framework for the adoption of BDA in South African financial institutions. The technology-organisation-environment (TOE) framework was used as the underpinning theory for this study based on which a conceptual framework was designed. A close-ended questionnaire was used to collect data from a South African financial institution in the Gauteng Province. Random sampling to select the 130 respondents that participated in the study. Results revealed that technological factors, technological characteristics, users' perception towards technology, organisational factors due to top management support, individual characteristics and BD characteristics are essential in BDA adoption. However, the results also indicated that organisational factors, organisational factors due to size and structure of the organisation and environmental factors were not significant in the adoption of BDA. This study contributes to the studies of BDA adoption in organisations in developing nations. The degree of influence that different factors have on adoption of technologies differs depending on the context, future studies can leverage these findings to extend research in BDA adoption. This study recommends that future research expand data collection to include more organisations that are categorised as financial institutions to properly generalise the study's findings.

KEYWORDS:

Big data analytics, technology adoption, organisation, financial institutions.

DECLARATION

I, **Mzwandile Dlamini**, declare that this research report 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 the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: Mzwandile Dlamini **Signature**: 

Signed at …Randburg…

On the ….28th…. **day of** …May… 2024

DEDICATION

This research paper is dedicated to my late Mom who always encouraged me to make the most of learning opportunities.

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LIST OF ACRONYMS

4IR	Fourth Industrial Revolution
BDA	Big Data Analytics
IoT	Internet of Things
RFID	Radio Frequency Identification

GLOSSARY

Adoption	This refers to the acceptance of an innovation, technology, or product. Organisations adopt IT innovations to sustain their competitive position as well as to create competitive advantage.
Big data (**BD**)	This refers to any data that cannot be handled in the traditional manner regarding collection, storage, processing, or analysis. It is characterised by high volume, velocity, and variety.
Big data analytics (**BDA**)	This is the process of examining enormous data sets to find patterns, undiscovered correlations, market trends, user preferences, and other useful information that was previously inaccessible to analysis using conventional technologies.

CHAPTER 1. INTRODUCTION

This first chapter introduces the concept of big data analytics (BDA) and why there has been an increase in the amount of data generated within organisations. The chapter then discusses the background of the study and highlights challenges faced by financial institutions that necessitates them to adapt to BDA. The problem that this study intended to address is highlighted based on which the research objectives are outlined. This is followed by the discussion of the motivation of the study. Lastly, the chapter gives an outline of the overall dissertation by briefly highlighting what each chapter presents.

1.1 Introduction to the field of study

BDA has attracted a lot of interest from business and researchers over the past few years. Organisations can collect and analyse BD with packaged services at a low cost (Morimura & Sakagawa, 2023). Using insights from BDA can speed up strategic decision-making and enable companies to react swiftly to customers' needs. BDA is intended to identify trends, connections, patterns, insights, or consumer preferences to enhance the decision-making process in business. BDA has been successfully used for various business functions, such as accounting, marketing, supply chain, and operations (Lee & Mangalaraj, 2022).

In businesses today a large amount of data are produced daily, and the information processed has increased tremendously. This is mainly attributed to the increase in the variety of devices that are used for data collection that include but not limited to mobile phones, wireless sensor networks, sensor devices on the internet of things (IoT), radio frequency identification (RFID) sensors, and many others (Berisha et al., 2022). In the fourth industrial revolution (4IR) era, any industry is characterised by the acceptance and use of new technologies. Technologies such as social media, mobile, cloud, BDA, along with the IoT have become noticeable digital disrupters that have essentially changed business models and value propositions of companies across industries (Mungai & Bayat, 2018).

Data are an important factor of production for financial institutions similar to conventional resources like capital and labour. BD and cloud computing are interdependent from a technical standpoint since BD depends on the distributed database and cloud storage technologies of cloud computing (Cheng & Feng, 2021). Conventional systems are inadequate for storing, processing, and analysing the large volume of data generated daily by financial activities (Poddar et al., 2023). With the proliferation of cloud-based BDA tools that can be accessed online from anywhere, many industries are adopting BDA to analyse this huge amount of data generated daily (Sun & Huo, 2021). BDA is used in various sectors including but not limited to financial services, education, healthcare and manufacturing due to the many benefits that it provides. According to Phan and Tran (2022), BDA offers different features and uses depending on the industry.

According to Matsepe and Van der Lingen (2022), investments in 4IR will help financial services organisations better deploy cutting-edge technologies that are essential to resolving their most pressing business issues. Investing in BDA solutions is considered costly and risky hence such initiatives should be able to provide value to the business in the form of information, transformation, strategic, and transactional value (Phan & Tran, 2022). An improvement in customer experience can be attained with the adoption of BDA in conjunction with other technologies to better understand customer behaviour and offering personalised products and services (Lutfi et al., 2022a). One of the most important aspects of competitiveness is understanding customer behaviour. Besides helping organisations better understand customer behaviour, BDA enables organisations to discover the unpredictable trends of their operations, customers, and market landscape (Lutfi et al., 2022a). These days, the question is not whether BDA should be adopted, but rather how to do it by understanding the factors that play a role in its adoption.

1.2 Background of the Study

Across all industries, there is clear evidence that the 4IR technologies are having a major impact on business (Matsepe & Van der Lingen, 2022). The 4IR has impacted business in various ways such as customer expectations, product enhancement, collaborative innovation, and organisational forms. Whether they are consumers or businesses, customers are at the core of the economy, which necessitates focussing on enhancing how customers are served (Schwab, 2017).

The big volumes of data gathered and processed have resulted in organisations acquiring and using BDA tools in their processes in order to make sense out of the generated data. World over, various businesses are increasingly becoming aware of the benefits of BDA hence the rise in the need for better analytics (Islam et al., 2023). In financial services, for instance, lot of consumer transactional, behavioural, and demographic data are held and stored. These types of operations are bound to generate a lot of data that need to be transformed into valuable business information. To make sense of this data, financial institutions need to become savvy with BDA in order to draw better insights so as to make better decisions needed for competitiveness (Nobanee et al., 2021).

Big data and advanced analytics are at the heart of financial services firms, hence it is essential for them to equip themselves with better skills needed to serve their clients while lowering operating costs and reducing credit, market, and operational risks (Moyo, 2022). Much as this is so, few models have been developed to inform how financial institutions could effectively adopt BDA, the tools to use, as well as to know the needed skills for this task (Matsepe & Van der Lingen, 2022). Additionally, the use of BD by financial institutions has been a key differentiator and success factor for most of them. Financial institutions could use BDA to improve customer experience, for fraud detection, risk modelling, credit risk analysis and to better serve customers through more accurate targeting and service delivery (Mogoale et al., 2022). This makes it imperative that there should be a contextualised framework to inform the adoption of BDA within financial services.

By implementing BDA, financial institutions can effectively handle a number of their challenges such as fraud, poor decision-making, delayed responses to customers, and loss of customers to competitors.

Constant threat of fraud is what most financial institutions are facing, identifying and preventing fraud is one of the most important problems facing them today. Through BDA large volumes of data can be analysed instantly and abnormalities can be detected faster using machine learning algorithms thus stopping fraudulent transactions (Hasan et al., 2023). Obtaining insight into the behaviour of customers is important for offering tailored services and enhancing their satisfaction. Financial institutions can use BDA to understand customer consumption patterns and preferences and use this information to make personalised offers based on their interests (Hasan et al., 2023). This not only improves customer satisfaction but also allows organisations to anticipate and avoid customer attrition. Complicated risk factors may not be appropriately captured by conventional methods, yet risk management is an essential component of financial operations (Dicuonzo et al., 2019). To examine a variety of data sources in order to assess risk more thoroughly and accurately, particularly credit and reputational risk, financial institutions can use BDA. To keep abreast of their competitors in the financial services industry entails a thorough comprehension of market developments and competitors. Organisations can use BDA to identify market trends and competitor activities and use these insights to gain a competitive edge (Horani et al., 2023).

1.3 Research Problem

In business today, enormous volumes of data flow in and out of organisations on a regular basis because of technological advancements, therefore it is vital to have quicker and more effective methods of analysing such data (Sharma et al, 2023). Overall, the 4IR is driving organisations to re-evaluate how they conduct business due to the unavoidable transition from basic digitalisation to innovation based on a combination of technologies (Kalema, 2022). This implies that organisation executives and senior leaders need to live up to this paradigm shift and adapt better ways of operations and innovativeness that leads to competitiveness (Islam et al., 2023; Schwab, 2017).

Around the world, several organisations gather, preserve, and assess information for a range of public and private benefits. According to Ganesh (2023), the increase in collection of both structured and unstructured data is a key component of the BD market, which is constantly expanding across the world. In South Africa, for example, the widespread adoption of sophisticated and simple-to-use BD solutions has become number one priority for most organisations and IoT of data are being collected (Ganesh, 2023). South Africa is considered an emerging economy with its own unique contextual factors, it is important to understand to what extent these factors influence the adoption of BD in financial institutions.

Parvinen et al., (2020) notes that data gathered and stored within organisations continue to grow exponentially and nowadays it is seen as a valuable asset that has the ability to impact industries through data analytics-driven practices and offerings. He, however, noted that much as this is so, there is still limited understanding of how many organisations can utilize this data especially the unstructured data since many transaction systems used can only analyse the structured data. Similarly, Brewis et al. (2023) allude that BD can increase an organisation's profitability and competitiveness by expanding market knowledge and strategic marketing insight. Obtaining meaningful information and competitive advantages from enormous amounts of data is of a high priority for most organisations, and BDA is a way of obtaining value from these large volumes of data, with the potential to enhance knowledge within an organisation (Pillay & Van der Merwe, 2021). However, literature shows that little has been done to inform how financial services could benefit from these new technologies of BDA as fewer frameworks have been developed to guide the adoption of BDA (Matsepe & Van der Lingen, 2022). More still, those frameworks that are available are too generic and are not contextualised to the South African financial services perspectives (Sharma et al, 2023).

With the growth in the amount and diversity of data that are received by organisations daily, it is imperative that they use BDA in order to extract value from this generated data. This study, therefore, sought to develop a framework for the adoption of BDA in South African financial institutions. The developed framework contributes to the theoretical understanding of BDA as well as to the adoption of technologies in other sectors in South Africa. South African organisations will be provided with insights about BDA adoption and its benefits, henceforth contributing to the practice of BDA in the South African context.

1.4 Research Objectives

This study sought to achieve the following objectives:

1.4.1 Major objective

The major objective of this study was to develop a framework for the adoption of BDA in South African financial institutions.

1.4.2 Specific objectives

To achieve the major objective of the study, the following specific objectives were set to be met.

1. To determine the factors influencing the adoption of BDA
2. To explore the benefits of BDA within organisations
3. To establish the theories needed for the adoption of BDA
4. To use the identified factors in the development of the framework for BDA

1.5 Rationale

Technology has disrupted the financial services industry and data have become an important part of financial institutions. In financial services BD can be used in various ways such as tracking customer behaviour, compliance analytics, analysis for fraud and operational analytics (Goyal et al., 2020). This implies that it is essential to analyse each, and every data generated within an organisation, whether structured or unstructured. Better analytics of the generated data is paramount in the drawing of insights that facilitate relevant decision making within an organisation (Pillay & Van der Merwe, 2021).

Governments, corporations, and other organisations are increasingly turning to BD as a new resource to discover patterns and produce insights. All types of organisations have come to value the capability to gather, store, and analyse BD (Vitari & Raguseo, 2020). Consequently, financial institutions are information-based and need better BDA than most of the organisations. This is because most of their day-to-day operations are based on analysing data in order for them to serve their stakeholders (Bansal et al., 2022). Additionally, financial institutions receive and generate enormous volumes of data, at high velocity, and from a variety of sources, to make sense of these data better analytics are required (Bansal et al., 2022). More so, the financial industry is characterised by intense competition, hence BDA is crucial for them to achieve a competitive advantage (Mikalef et al., 2020). Therefore, the framework that was developed by this study will guide financial institutions in drawing better insights from the generated data by adopting the BDA approaches and techniques leading them to competitiveness.

1.6 Delimitations of the Study

The scope of the study is limited to the adoption of BDA in South African financial institutions.

1.7 Assumptions

It is assumed that respondents will share an accurate reflection of what is currently taking place in their organisations. However, it is anticipated that some respondents might be uncomfortable sharing information about what is happening in their organisations.

1.8 Chapter Outline

Chapter 1: Introduction

This chapter introduces the research and gives the background of the study. The chapter also highlights the research problem and the objectives that need to be met in order to solve the research problem. It also articulates the rational of the study, the delimitations and assumptions.

Chapter 2: Literature Review and Theoretical Framework

This chapter reviews the literature on BDA, the uses of data and its benefits within the financial institutions. The chapter also discusses the theoretical foundations from which the conceptual model was derived. The chapter outlines the hypotheses that were subsequently evaluated to confirm the final model's design based on the conceptual model.

Chapter 3: Research Methodology

This chapter discusses the research design and methodology. It highlights the research approach, strategy as well as the methods of collecting and analysing data. The chapter also elaborates on the population of the study and gives reasons why that population was selected. Based on the population of the study the sampling techniques are explained as well as the methods that were used to select the sample size. Finally, the chapter discusses the reliability and validity of the study as well as the ethical considerations that were followed in collecting, analysing, and dissemination of the findings of the study.

Chapter 4: Analyses and Presentation of Results

This chapter presents the results of the study. The collected data are analysed quantitatively, and the suggested constructs of the conceptual framework are operationalised into hypothesis that are tested, and results presented in this chapter.

Chapter 5: Discussion, Conclusion and Recommendation of the Study

This chapter discusses the findings of the study and gives the implications in relation to theory and practice. The chapter also highlights those areas which the study ought to have done but for some reasons or the other were not accomplished. These areas are reported as the limitations of the study based on which the recommendations for future research are given. Finally, the chapter gives the conclusion of the study.

CHAPTER 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

This chapter unpacks the existing literature of BDA, it provides definitions of concepts, namely BD, and BDA, and discusses the existing literature on them. The uses of BDA in financial institutions, its benefits, challenges, and factors influencing its adoption are discussed. Based on the identified factors and related studies the underpinning theories are highlighted and discussed, and the conceptual framework is designed. From the conceptual framework, the hypotheses of the study are derived.

2.1 The Concept of Big Data

The increasing use of technologies such as smart phones and social media has resulted in a high generation of raw data and globally every person is creating an extensive and growing digital record known as BD (Maroufkhani et al., 2020b). Organisations have large amounts of data that come from transactions data, clickstream data, video data, voice data, social networks, emails, phones, and other sources (Sun & Huo, 2021). On the other hand, the use of social media platforms such as Facebook, Twitter, LinkedIn, and YouTube generate huge amounts of data in distinctive formats, and it is practicality difficult to analyse this data the current conventional data analysis tools (Singla et al., 2020).

Big data can be defined as the complex huge amount of data generated from multiple diverse sources including sensors, social media, IoT and administrative services (Singla et al., 2020). As these data are generated from multiple sources, it can be in the form of structured, unstructured, or semi-structured. According to Vassakis et al. (2018), unstructured data are expanding faster than structured data, consequently, new kinds of processing abilities are required to get data insights that enhance decision-making. BD can also be defined as a sizeable dataset that cannot be organised or analysed by established databases (Baig et al., 2019). BD can be categorised by the following characteristics volume, velocity, variety, veracity, and value (Abdalla, 2022). These characteristics are explained as;

- Volume: The growth in data has been due to factors such as growth in convergences of technologies, mobile data use, social media, connected devices and cloud storage to name a few. Abdalla (2022) mentions that petabytes and terabytes are about the size of data, volume refers to the large quantity of information generated and stored.
- Velocity: This is defined as the high speed at which the data are generated and processed (Gupta, 2023), it is the frequency at which data are generated. As data are being generated at a fast rate there has been a need for it to be analysed in real-time.
- Variety: This refers to the different types of data collected (Walker & Brown, 2019). It characterises the increasing assortment of data generating sources and formats. Modern technological developments enable organisations to use various sorts of structured, unstructured, and organised information (Rawat & Yadav, 2021).
- Veracity: This refers to data reliability and accuracy. Data collection has data that are contaminated and not accurate (Amalina et al., 2019).
- Value: If stored and analysed properly, the data can provide valuable insights. A high value is produced by evaluating large amounts of data, which in turn improves the knowledge drawn from the data (Gupta, 2023).

2.1.1 Big Data Analytics

The increase in the amount of data and the velocity at which it is generated, has necessitated the quick transformation of data into useful knowledge by analysing it also known as BDA. Gangwar (2018) defines BDA as approaches, technologies, systems, procedures, tools, and applications that enable organisations to more quickly, effectively, and efficiently extract important business data from irrelevant data. The tactics regularly combine text analytics, audio analysis, video analytics, social media analytics, and predictive analytics.

Big data analytics relates to extracting value from data, facilitating finding specific patterns that can support targeted decision-making (Moraes et al., 2022). According to Walker and Brown (2019), BDA can be outlined as the systems, methods, equipment, means, techniques, and processes utilised to gather, store, and analyse BD in order to provide useful insights. Big data analytics involves data management, statistical analysis, and visualisation tools that help organise and integrate data to reveal patterns, relationships, and other useful insights (Singla et al., 2020; Vassakis et al., 2018).

According to Pillay and Van der Merwe (2021), BDA can be used to enhance business decision-making resulting in improved operations performance, and competitive advantage. Given this situation, there are two stages in the process of gaining insights from BD and these are data management and data analysis. Data analysis refers to the methods and procedures for analysing and interpreting the insights derived from BD, whereas data management refers to the processes and technology for data collection, storage, mining, and preparation for analysis (Vassakis et al., 2018), as shown in Figure 2.1. By making sense of the data for various analytical challenges, including descriptive analytics, predictive analytics, and prescriptive analytics, BDA can improve decision-making and increase organisational productivity (Belhadi et al., 2019).

Figure 2.1: Process for generating insights from BD

Source: *Vassakis et al, (2018)*

There are different analytical methods that can be used to extract insights from the data. The BDA techniques can be categorised into four, ranging from descriptive, inquisitive, predictive, and prescriptive.

- Descriptive analytics: Based on historical and current data, it seeks to answer the question of ‘what happened’ or alert on what is going to happen. Tools such as dashboards, charts and graphs are used (Belhadi et al., 2019).
- Inquisitive analytics: This examines ‘what happened’, in order to uncover the root cause of a problem (Tamym et al., 2023). Therefore organisations can avoid past mistakes and make better decisions.
- Predictive analytics: This is about forecasting the future utilising past data. Data mining and machine learning are used to examine past and present data to envisage what is likely to occur (Vassakis et al., 2018). It is commonly used in prediction of customer behaviour, marketing and preventing risk.
- Prescriptive analytics: This optimises the process models produced by predictive analytical models. Prescriptive analytics is used to predict the future and finding the best course of action (Tamym et al., 2023).

In addition, there are other methods which are used to analyse data. A subset of the tools accessible for BDA is represented by the methodologies listed below.

- Text analysis – sentiment analysis notifies firms to areas where customers are unhappy or keen to switch to other options, allowing them to take pre-emptive actions (Al-Shiakhli, 2019). Customer service and marketing are key areas where this is used.
- Audio analytics or speech analytics using technical approaches – these can be classified into transcript-based systems and phonetic-based systems which work with sounds or phonemes (Orenga-Roglá & Chalmeta, 2018). Main application areas are customer call centres.
- Social media and social network analysis (SNA) – these methods analyse data from social media. Social media uses text mining or sentiment

analysis to uncover valuable patterns and user information. SNA is interested in social entity relationships by measuring who shares what information and with who (Orenga-Roglá & Chalmeta, 2018). Marketing is the primary application area.

- Data visualisation – it can even be used by decision-makers with less understanding about data because it presents the information graphically before thorough analysis. Advanced data visualisation offers more opportunities for BDA growth since it facilitates data analysis at numerous levels by utilising human perceptual and reasoning abilities (Al-Shiakhli, 2019).

2.1.2 Benefits of BDA

According to Raguseo (2018), common benefits of BDA include transactional, strategic, transformational, and informational. Transactional benefits refer to investments that support operational management and which are able to cut the costs sustained by companies. Strategic benefits are benefits that change how businesses compete or the nature of their products are considered strategic. Some products may undergo changes in their features (Davenportis, 2014). Transformational benefits refer to the results of changes that a firm has to make to the structure and to the capacity of implementing a technological investment. Big data solutions enable some companies to operate in new value chains in which they were not previously. Informational benefits are those that provide information and communication that can be used to improve decision-making in a company. With BDA, companies are able to make improvements in data management and have easier access to data (Raguseo, 2018).

Through BDA it is possible to establish useful links with other organisations (Abraham et al., 2019). In South Africa for instance, credit bureaus maintain data on consumers and business, keeping updated consumer profiles on millions of customers monthly. Banks rely on this data to assess the credit worthiness of consumers before they make decisions whether to extend or decline credit and the interest rate payable.

Big data analytics advancements in particular, along with the ever-growing volume of digital trace data, open up new opportunities for service innovation. According to Lehrer et al., (2018), organisations can gain insightful knowledge by assembling their customers' digital traces into an in-depth understanding of an individual's daily life by using the effective methods and tools that BDA offers for collecting, processing, and analysing massive amounts of trace data. For instance, Discovery Insure has Vitality Drive which is a behaviour-centred driver programme that rewards plan holders for driving well. Vitality Drive uses the newest vehicle telematics technology to gather data on driving habits, including acceleration, braking, turning, speeding, night-time driving, distance travelled, and mobile phone use (Discovery Insure, 2022).

Big data analytics allows companies to examine customer reviews and sentiment analysis. Organisations can receive information about how customers feel towards something from various social media websites in text format. Once these feelings are noted they can be categorised as positive or negative, and they could be used to provide clients with relevant services based on their comments (Bansal et al., 2022). Marketing professionals may find that BDA with a focus on sentiment analysis is a beneficial technique for gaining systematic customer knowledge and creating effective marketing initiatives (Rejeb et al., 2020).

Using predictive analytics improves business performance. This is supported by Brynjolfsson et al. (2021), who found that adopting predictive analytics is linked with statistically and commercially significant increases in production. Big data analytics can also be used for predictive maintenance. For gathering, storing, and analysing data produced by user devices and network devices like routers, switches, base stations, and so on, network operators now use BDA tactics. With this data, operators are able to monitor network performance to guarantee functioning without issues (Rabhi, 2019).

Crisis management requires planning and quick response to situations before they escalate. AL-Ma'aitah (2020) mentions that BDA plays an important role in the different phases of crisis management such as crisis preparedness, response, and recovery. Through integrating and coordinating data from multiple sources BDA contributes to detection of early warning signs for various crises. The data from mobile phones and social media enables management to get valuable insights from consumers and by analysing the data, they are able respond effectively to a situation (AL-Ma'aitah, 2020).

Since customer self-service and product customisation are potential sources of customer data, BDA makes product or service personalisation possible and simpler (Rejeb et al., 2020). The deeper understanding of customers on a personal level enables the design of personalised products and personalised communication. Using BDA organisations can obtain real-time data about customers' opinions, product evaluations, and suggestions and be able to improve their understanding of unmet customer needs (Rejeb et al., 2020). This allows organisations to improve performance and eventually enrich customer service.

Big data analytics make it possible to draw conclusions from information obtained from research, clinical care settings, and operational settings to create evidence for better care delivery (Iyamu, 2020). In healthcare, patterns and relations can be uncovered from analysis of BD and in addition to predicting outcomes. From the patient point of view, data analytics can support patients by giving them more accurate information that can aid in decision-making through the study of personal data (Iyamu, 2020). Patients also benefit through care that is supported by faster diagnosis and more suitable medicine.

Data monetisation happens when organisations generate additional income from current data sources to create useful information, insights, and observations (Ofulue & Benyoucef, 2022). Data monetisation also comprises leveraging insights to create value-added features for other clients (i.e., extended data wrapping). For instance, Facebook generates revenue by offering data analytics features to advertisers based on user data on its social network platform (Quach et al., 2022).

2.2 Financial Institutions

The enormous availability of BD and the advancement of its analytics has resulted in organisations having to change the way they manage their operations, customers, and business models. This section examines the benefits and challenges presented by BDA in financial institutions. In addition, the factors that influence the adoption of BDA are discussed.

2.2.1 Big Data Analytics in Financial Institutions

Using insights derived from BDA financial institutions can forecast, with improved precision, customer needs and improve customer experience. There are several uses and benefits of BDA within financial institutions. These include;

a. Customer Acquisition and Retention

Customers have so many options they can choose from in the South African financial services sector, therefore, customer acquisition and retention are crucial. Big data enables financial institutions to understand consumers' consumption patterns and behaviour, simplifying their wants and requirements (Hasan et al., 2021). Thus, companies can more effectively recognize promising leads and create solutions to turn those leads into customers. Based on customers' past consumption patterns and behaviour, financial institutions are able to provide incentives that are specifically tailored to their needs in order to keep their current clients (Hasan et al., 2021).

b. Fraud Detection

Financial institutions are characterised by a lot of transactions and their business is monetary in nature, making them more vulnerable to fraud. For any strategy developed to detect and inhibit fraud, BDA have become a crucial part of it

(Tekaya et al., 2020). Algorithms based on real-time transaction data to develop more precise and less invasive fraud detection techniques are used by financial institutions (Hasan et al., 2021). These systems use huge amounts of data generated from several sources at high speed. In addition, BD enables the prevention of unauthorised transactions by offering a protection and security level for financial institutions (Hasan et al., 2021)

c. Customer Segmentation and Marketing

Big data enables financial institutions to use an array of individual characteristics to segment consumers into distinct groups and make personalised offers based on their interests. Big data analytics is used by financial institutions for targeted advertising and cross-selling of their products (Abraham et al., 2019). Financial institutions are segmenting their consumers more effectively and tapping into new market segments because of insights from customer data. Financial institutions can more effectively target their clients with appropriate marketing initiatives suited to consumers' needs, thanks to customer segmentation (Hasan et al., 2021). Spending habits, credit history and browsing history can be analysed using BDA and individual customers targeted with personalised offers (Poddar et al., 2023).

d. Personalisation

Financial institutions have always relied on personalised connections between consumers and officials at branches to know and understand the demands of their customers (Abraham et al., 2019). Personalisation can be difficult to maintain with many clients. Nowadays, BDA allows financial institutions to offer personalised services to millions of customers. In addition, BDA allows financial institutions to offer personalised services to individual customers. According to Mogoale et al. (2022), BDA is also used by financial institutions for targeted advertising and cross-selling of their products. Big data enables financial institutions to use an array of individual characteristics to segment consumers into distinct groups and make personalised offers based on their interests.

e. Risk Management

One of the valuable assets of a financial institution is data, and BDA has made it possible to manage risk through development of predictive indicators obtained from diverse data sources (Hasan et al., 2021). For financial institutions to visualize possible risk, it is extremely crucial to connect data from diverse systems. By examining data such as credit reports, spending patterns, and repayment rates of credit applicants, BDA tools help financial institutions gain deeper insights into the behaviours of their customers. Through these insights they can determine the risk that a customer will miss multiple payment deadlines or go into default on a loan (Pérez-Martín et al., 2018).

2.2.2 Challenges of Big Data Analytics in Financial Institutions

Despite the obvious advantages of BD in financial institutions, there are numerous obstacles that may prevent its widespread implementation. It is important to not only associate BDA with positive consequences, but there may also be challenges as well.

Building massive data sets with private information is part of using BD in financial organisations and how to preserve this privacy is a big challenge (Abraham et al., 2019). There needs to be transparency on what information companies have on customers and what it is used for. The data come from various sources and are decentralised, therefore analysing heterogeneous data source has become a privacy and security issue because of the communication with other external systems (Amalina et al., 2019).

Security is cited as a major issue in BDA adoption and among the challenges are the distributed nature of large BD which is complex and susceptible to attack, it is also vital to make sure that the source in not compromised by any attacks (Amalina et al., 2019). Within the past five years there have been malware attacks, ransomware attacks and Distributed Denial of Service (DDoS) attacks targeted at financial institutions, credit bureaus and debt recovery solutions service providers as per communication from the South African Banking Risk Information Centre (SABRIC). As many as 24 million South Africans and 793 749 business entities personal information was exposed to a suspected fraudster when Experian experienced a breach (SABRIC, 2020). TransUnion South Africa was hacked and through the misuse of an authorised client's credentials, data belonging to the bureau were obtained. The personal information obtained included names and ID numbers (SABRIC, 2022).

Many of the financial institutions that were established many years ago have data that are generally dispersed across legacy systems. These legacy systems normally do not integrate very well with the cloud-based systems. Extracting data from old systems and configuring it for modern analytics can be a costly and time-consuming exercise (Iron Mountain, 2023). Data sets can be so large and make it difficult to know where to begin from and what to look for. Having more data does not always result in having better analysis. It can be possible to find correlations between variables but tough to differentiate correlation from actual causation (Abraham et al., 2019).

A lack of employees with the correct data analytics skills and experience, especially from emerging economies, is another challenge. What is needed are employees who can cross functional boundaries or translators between analytics and the business (DeHoratius et al., 2023). The scarcity of internal analytics skills, therefore, results in the hiring of experienced data scientists and data engineers at a high cost (More & Moily, 2021). Training employees and outsourcing can be used in such situations.

Financial institutions are obliged to adhere to a lot of regulatory requirements in relation to consumers' rights over the processing of their personal data and its use. For instance, the Protection of Personal Information Act (POPIA) provides data privacy rights and information protection for South Africans. The Information Regulator has the authority to oversee and enforce public and private entities' adherence to the provisions of the POPIA (Information Regulator, 2023). Failure to observe such regulations may result in hefty fines to offending entities.

2.2.3 Factors Influencing BD Analytics Adoption in Financial Institutions

In this section we discuss the factors that play a role in BDA adoption in financial institutions.

a. Perceived compatibility

Innovation is considered compatible with an organisation only when it is perceived as coherent with its prevailing business processes, practices, and value system (Merhi & Harfouche, 2023). Adoption of BDA necessitates a system that is suitable to the IT capabilities and requirements in existence in the organisation (Sekli & De La Vega, 2022). The rise in adoption rates is significantly influenced by compatibility. New technology should be interoperable and user-friendly (Baig et al., 2019). Innovations that conflict with the current organisational standards and values are less likely to be adopted or will have a slow adoption rate. Equally, the higher the perceived compatibility of BDA, the quicker the adoption rate (Walker & Brown, 2019).

b. Perceived benefits

The definition of perceived benefits is the advantages that an organisation believes using the innovative technology can provide it (Merhi & Harfouche, 2023). In financial services BDA has been shown to have many such benefits as enabling the design of personalised solutions to customers and efficient risk management to prevent fraud and financial losses (More & Moily, 2021). In addition, BDA assists in customer segmentation and marketing (Abraham et al., 2019). Some benefits, such as increased customer satisfaction, can be indirect.

c. Data quality and complexity

Integrating data from different sources and guaranteeing their quality is challenging because users are more comfortable to use BDA systems when they know that the obtainable data for analysis is of high quality, accurate and current (Chen at al., 2022). Organisations are increasingly aware of these challenges and are applying data processing etiquettes to influence data quality. The rationale is that the results of any analysis and functionalities of any system are impacted by the quality of this data (Merhi & Harfouche, 2023). Accuracy, timeliness, integrity, and readability are factors that can be used to gauge data quality. An improvement in any dimension can possibly influence users to adopt BDA systems (Chen at al., 2022). Therefore, data quality should be among the top priorities in BDA adoption and implementation. Complexity is the extent to which innovation is thought to be comparatively challenging to utilise and comprehend (Sekli & De La Vega, 2022).

d. Privacy and security

Compared to traditional data environments, the volume, velocity, and variety characteristics of BD contribute to the distinctive threats that magnify the challenges for handling BDA security (Walker & Brown, 2019). Privacy and security will not only impact the BDA adoption process but can destroy the company reputation (Baig et al., 2019). Most companies invest a large part of their budget in data security using encryption, tokenization, and many others (Cuenca et al, 2020). Data privacy policies also help clarify the correct use of data.

e. IT infrastructure

IT infrastructure is the foundation of most business operations especially now in the 4IR era. A strong technical infrastructure enables the adoption of BDA, which has been the strength of most of the business that have taken it on (Behl et al., 2019). A dynamic infrastructure is required to handle the complexity and computing power needed to collect and process BD. Three resources namely human, intangible, and tangible make up an IT infrastructure (Merhi & Harfouche, 2023). The human resources comprise IT and managerial skills while intangible resources entail knowledge assets. Technological components such as hardware, servers, middleware, and networking pertain to tangible resources.

f. Management support

A supportive climate from top management is a vital determinant of adoption and implementation of technology in organisations (Merhi & Harfouche, 2023). Support from senior management is crucial since it directs the re-engineering of business processes, assists in assigning the necessary resources, and facilitates the integration of services (Chaurasia & Verma, 2020). Lack of management support can be a hinderance to provision of resources and capital which can delay the adoption process. Management support is a very important factor in the adoption of BDA (Baig et al., 2019). In the context of BDA, this support is crucial because sufficient and well-coordinated resources are needed for the necessary data integration and infrastructure (Sekli & De La Vega, 2022).

g. Organisational culture

Organisational culture includes shared fundamental beliefs, values, norms, behavioural patterns, and artefacts as defined by a pattern of shared basic assumptions that a group learnt through solving challenges of external adaptation and internal integration (Sabharwal & Miah, 2021). Culture influences the interaction among employees and their work environment by outlining the proper behaviour for various scenarios (Merhi & Harfouche, 2023).

h. Human resources expertise

Knowledge and abilities needed to carry out activities connected to BD are from the human resources. Lack of employees with the necessary knowledge on how to use the technologies have a negative impact on BDA adoption. In the case of BDA usage, the availability of experts with the proper IT skills and abilities is essential (Walker & Brown, 2019). Innovation in technology is employed and sustained in most instances by human resources and having enough of them is essential for BDA adoption.

i. Industry competition

The external influences that emanate from the environment surrounding the organisation such as technological advancements, industry and competitors can influence the decision of organisations to adopt and implement technology (Merhi & Harfouche, 2023). The need to stay ahead of competitors and meet the evolving client expectations drives the use of BDA. Organisations use analytics to guide data-driven decision-making, identify market trends, streamline processes, and improve customer experiences in order to gain a competitive edge (Horani et al., 2023). Organisations are persuaded to adopt BDA by the pressure of industry competition.

j. Vendor support

The availability, regularity, and technical support provided by the vendor influence the decision to adopt any technology or technological service (Behl et al., 2019). Vendor support is even more critical when the technology is complicated compared to for less complicated technologies (Merhi & Harfouche, 2023). When it comes to BDA, assistance from specialised vendors enables the development of the skills required for its effective application (Sekli & De La Vega, 2022). Organisations can enhance their capacity for innovation by gaining knowledge from suppliers which is a significant contributing factor to the adoption of BDA (Maroufkhani et al., 2020a).

k. Regulations and laws

Policy makers around the world have begun discussions of ways to meet the new challenges associated with BD and to regulate its use (Abraham et al., 2019). Regulations have been released by several countries to enhance consumers' rights over the use of their personal data and coupled with hefty fines and penalties for wrongdoers. In the South African context, POPIA is aimed at protecting the privacy of individuals. Organisations are expected to process personal information only for legitimate business processes, and consumers may object or withdraw consent at any time. This might have an impact on businesses who are wanting to personalise communication to their customers. Organisations need to factor in regulations such as POPIA in their use of BDA. The summary of factors influencing BDA are as summarized in Table 2.1.

Table 2.1: Summary of factors influencing BDA adoption

Factor	**Explanation**	**Source**
Perceived compatibility	Adoption of BDA necessitates a system that is suitable to the IT capabilities and requirements in existence in the organisation.	Sekli & De La Vega, 2022; Baig et al., 2019
Perceived benefits	In financial institutions BDA has been shown to have many such benefits as enabling the design of personalised solutions, segmentation and efficient risk management to prevent fraud.	More & Moily, 2021
Data quality and complexity	Accuracy, timeliness, integrity, and readability are factors that can be used to gauge data quality. An improvement in any dimension can possibly influence users to adopt BDA systems.	Chen at al., 2022
Privacy and security	The volume, velocity, and variety characteristics of BD contribute to the distinctive threats that magnify	Walker & Brown, 2019

Factor	Explanation	Source
	the challenges for handling BDA security.	
IT infrastructure	A strong technical infrastructure enables the adoption of BDA, which has been the strength of most of the business that have taken it on.	Behl et al., 2019
Management support	Support from senior management is crucial since it directs the re-engineering of business processes, assists in assigning the necessary resources, and facilitates the integration of services.	Chaurasia & Verma, 2020; Baig et al., 2019
Organisational culture	Culture influences the interaction among employees and their work environment by outlining the proper behaviour for various scenarios.	Merhi & Harfouche, 2023
Human resources expertise	The availability of experts with the proper IT skills and abilities is essential for BDA adoption.	Walker & Brown, 2019
Industry competition	Organisations are persuaded to adopt BDA by the pressure of industry competition.	Merhi & Harfouche, 2023

Factor	Explanation	Source
Vendor support	The availability, regularity, and technical support provided by the vendor influence the decision to adopt any technology or technological service.	Behl et al., 2019; Sekli & De La Vega, 2022
Regulations and laws	Regulations have been released by several countries to enhance consumers' rights over the use of their personal data.	Abraham et al., 2019

2.3 Related Work

Walker and Brown (2019) conducted a study on a large telecommunication organisation in South Africa. The study aimed at establishing factors that influence BDA adoption process in organisations. The technology, organisation, and environment model (TOE) (De Pietro et al., 1990) was combined with elements from a BD adoption model by Chen et al. (2015) whereby themes relating to the adoption of BDA in organisations were identified. The adoption of BDA was confirmed to be influenced by five technological aspects namely; relative advantage, complexity, compatibility, trialability, and data quality. Their study further indicated that four organisational elements influence the adoption of BDA and these are top management support, human resource expertise, business and information technology (IT) alignment, and organisation size (Walker & Brown, 2019). More still their study indicated that environmental factors of competitive pressure, data privacy, vendor support, IT fashion, and regulatory requirements also play a significant role. Additionally, factors of paradigm shift and complexity tolerance were also found significant. Their study recommended that future research should examine these factors in a different context and their influence may change from one perspective to another.

To identify the factors influencing the adoption of BDA among Korean businesses, Park and Kim (2021) used TOE as an underpinning theory in their quantitative research. Data was collected from 50 experts and 226 businesses and analysed using analytic hierarchy process (AHP) and regression analysis. The findings of their study revealed that benefits of BD, technological capabilities, financial investment know-how, and data quality and integration are the most important determinants of adoption of BDA (Park & Kim, 2021). Other factors included government backing and policy, security, and management support for BDA. Their study recommended that, much as the identified factors could be generic, enough contextualisation is needed as there might be differences among sectors and acceptance of BDA might be impacted by different factors specific to that industry.

Wahab et al. (2021) did a quantitative study through the lens of the TOE model to identify the factors affecting BDA adoption in the Malaysian warehousing sector using partial least squares structural equation modelling (PLS-SEM). The findings revealed that relative advantage, technological infrastructure, absorptive capability, and government support influence the levels of BDA adoption, whereas industry competition appeared to be of no major influence. It was found that warehousing firms more likely to adopt BDA were those that placed high priority on operational excellence, ICT infrastructures, and technology assimilation. Their study recommended that future research should consider enlarging and confirming the framework's adaptability to be contextually implemented for various countries and sectors.

To determine the drivers of BDA in the context of a developing economy, Lutfi et al. (2022b) conducted a quantitative study to examine the influence of organisational and environmental factors on BDA adoption in the Jordanian small and medium enterprises (SMEs) context, using PLS-SEM. Their study employed a composite model of TOE and diffusion of innovation theory (DOI) as the theoretical foundation. The findings indicated that the relative advantage, complexity, security, top management support, organisational readiness and government assistance influence the adoption of BDA, whereas competitive pressure and compatibility seemed to have little influence. Unlike their study that focused on SMEs, the current study is focusing on larger financial organisations, hence the identified factors by Lutfi et al. (2022b) may all be significant, or their influence may reduce in larger organisations.

Youssef et al. (2022) explored factors affecting retailers' adoption of BDA across three different countries by using a survey questionnaire to collect data from managers and decision-makers in the retail industry. Structural equation modelling was used to analyse the responses of 2278 respondents. The results showed that factors such as security worries, outside backing, top management support, and a culture of logical decision-making have a bigger impact on BDA adoption in established nations like the UK than in developing nations like the UAE and Egypt (Youssef et al., 2022). However, the adoption of BDA in the UAE and Egypt was found to be more influenced by the level of competition and company size. Lastly, human factors such as staff competencies and understanding of information systems have a significant impact on BDA adoption in Egypt than in the UK and UAE. Their results showed that a "one-size-fits-all" strategy may not apply when it comes to technology adoption as different users may have different social-technological backgrounds. More still the advancement of technology in developing countries may not be equally compared with that of developed countries. This finding signifies the importance of contextualisation and putting factors of culture into consideration (Mogoale et al., 2022).

Al-Dmour et al. (2023) conducted a quantitative study to investigate the variables influencing Jordanian commercial banks' use of BDA applications to enhance their performance. Their study used TOE as the theoretical underpinning framework. The findings of their study indicated that TOE could explain 61% of the variation in BDA applications where its constructs are used to assess commercial banks adoption of technology (Al-Dmour et al., 2023). In their study, they further indicated that the most significant predictor of technology use by banks are organisational aspects, followed by technological and the users' characteristics. Much as their study revealed the prediction power of TOE constructs, it gave no attention to contextualisation that had been echoed by various researchers (Mogoale et al., 2022; Park & Kim, 2021).

2.3.1 Identified gaps, similarities and differences

According to a review of the literature, there is limited research on BDA adoption in South Africa compared to other nations. The literature indicates that fewer frameworks have been developed to guide the adoption of BDA in financial institutions and how financial institutions could benefit from these new BDA technologies. There is also a lack of contextualisation of BDA adoption to the South African financial institution landscape. Similar to the current study, the study by Walker and Brown (2019) aimed at establishing factors that influence the BDA adoption process in organisations using the TEO framework. Instead of a single case study in which few participants were interviewed, the current study sought to examine these factors in a different context using the quantitative approach.

The study by Park and Kim (2021) used TOE as an underpinning theory in their quantitative research similar to the current study. The current study sought to contextualise the identified factors to financial institutions as there might be differences across industries. Through the lens of the TOE framework, Wahab et al. (2021) did a quantitative study similar to the current study to identify the factors affecting BDA adoption in the Malaysian warehousing sector. The study sought to investigate how industry competitiveness affects the adoption of BDA at a different setting which was found to have little impact on the warehousing sector. The aim of the study by Lutfi et al. (2022b) was to identify the factors that influence BDA adoption in in a developing economy using the TOE framework similar to the current study. The current study focuses on larger financial institutions rather than SMEs meaning that the factors identified by Lutfi et al. (2022b) may all be important or their influence may be less in larger organisations.

Youssef et al. (2022) explored factors affecting retailers' adoption of BDA across three different countries by using a survey questionnaire similar to the current study. The current study sought to identify the most relevant variables influencing BDA adoption in financial institutions in South Africa. The quantitative study by Al-Dmour et al. (2023) used TOE as the theoretical underpinning framework to investigate the variables influencing Jordanian commercial banks' use of BDA applications to enhance their performance similar to the current study which also looked at financial institutions.

2.4 Theoretical Foundations

The adoption of BDA has increased over the past few years and many models that seek to study adoption of technology in the context of both individual and organisational level do exist (Oliveira et al., 2011). According to Aboelmaged and Mouakket (2020), the most commonly used theories and models in BDA adoption research are Dynamic Capabilities (DC), Resource-Based View (RBV), Technology Acceptance Model (TAM), Diffusion of Innovation (DOI), and Technology-Organisation-Environment Framework (TOE). From the factors identified in the literature and related work, this study used TOE as its underpinning theory since it is capable of working as a shell to accommodate the identified factors that influence BDA.

2.4.1 Technology-Organisation-Environment

The TOE model was developed by De Pietro et al. (1990) to explain the adoption and use of technology within organisations. TOE has been popularly used in various studies such as cloud computing, blockchain, social media marketing, IoT (Maroufkhani et al., 2023) since it allows the accommodation of various factors that influence the adoption and use of technology. Additionally, other researchers such as Lutfi et al. (2022b) have extended TOE to include other variables that play significant roles in technology adoption. In the case of this study, variables like individual characteristics and BD characteristics were included to inform the conceptual framework.

2.4.2 Conceptual Framework

Based on the identified factors in the literature, the following factors are classified into relative categories of organisation, technology with attribute, environment, individual characteristics, and BD characteristics to inform the development of the conceptual framework that is demonstrated in Figure 2.2.

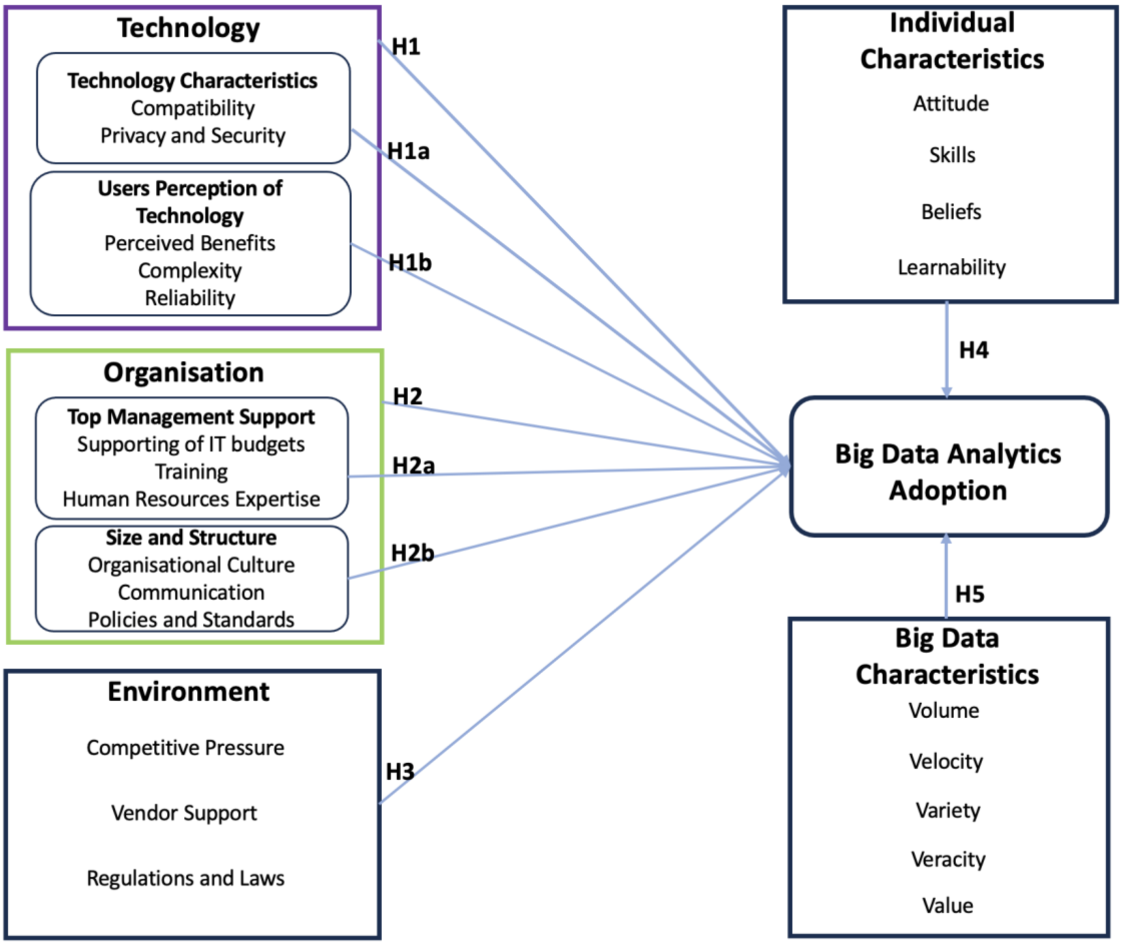

Figure 2.2: Conceptual framework

2.4.3 Operationalisation of the constructs and hypothesis development

Using the research model and the factors mentioned in the literature, nine hypotheses were formulated as demonstrated in Figure 2.2.

a) Technological context: The technological constructs refer to the endogenous and exogenous components of a technology that are essential to its adoption (Sekli & De La Vega, 2022). In this study the technological context was looked at from two different perspectives, namely technological characteristics, and users' perception of technology. Based on these two factors, the first (**H1**) hypothesis and its sub hypotheses (**H1a** and **H1b**) were derived.

H1: Technological factors influence the adoption of BDA.

H1a: Technological characteristics influence BDA adoption in financial institutions.

H1b: Users perception towards technology influence BDA adoption in financial institutions.

b) Organisational context: Organisational variables pertain to the structural facets of an organisation that have the potential to impact the adoption of technology (Sekli & De La Vega, 2022). In this study, the organisational context was examined from two angles, namely top management support and size and structure. From this construct the second hypothesis (**H2**) and its sub hypotheses (**H2a** and **H2b**) were suggested.

H2: Organisational factors influence the adoption of BDA.

H2a: Organisational factors due to top management support influence the adoption of BDA.

H2b: Organisational factors due to size and structure of the organisation influence BDA adoption in financial institutions.

c) Environmental context: This construct relates to the environmental surroundings that the organisation is sensitive to and are part of its evolving external environment (Lutfi et al., 2022b). Its constructs are competitive pressure, vendor support and laws and regulations. From this construct a third hypothesis (**H3**) was formulated.

H3: Environmental factors influence the adoption of BDA.

d) Individual characteristics: This concept relates to the characteristics and personality types of technology users that can lead them to believe that the adoption of BDA is necessary. These characteristics include attitude, skills, beliefs, and learnability. These characteristics may make individuals view BDA tools as easy to use and improve the quality of their work. From this construct a fourth hypothesis (**H4**) was theorized.

H4: Individual characteristics influence the adoption of BDA.

e) Big data characteristics: BD is a term used to describe massive datasets that are too big to manage or analyse with traditional databases (Baig et al., 2019). Big data is characterised by 5V's namely volume, velocity, variety, veracity, and value. From this construct a fifth hypothesis (**H5**) was derived.

H5: BD characteristics influence the adoption of its analytics.

2.5 Summary

The chapter discussed the concepts of BD and BDA and its benefits. The chapter also discussed the uses of BDA in financial institutions, challenges of BDA in financial institutions, and factors influencing its adoption in financial institutions. In addition, related studies and the theoretical foundations from which the basis of the conceptual model was developed were discussed. Lastly, the constructs of the conceptual model and hypotheses were developed.

CHAPTER 3. RESEARCH DESIGN AND METHODOLGY

This chapter discusses the research design and methodology that were followed while conducting this study. The chapter is divided into sections namely; research design, philosophy, paradigm, approach, strategy, data collection methods, population and sampling, data analysis, reliability and validity as well as ethical considerations.

3.1 Research Design

A research design demonstrates the flow of research and is considered as the blueprint of research (Creswell & Creswell, 2018). This study first reviewed the literature relating to BDA adoption in financial institutions and identified the challenges from which the understanding of the research problem was enhanced. More still further literature was reviewed to identify influential factors necessary for the BDA adoption model. Based on the identified factors the conceptual framework was modified and then used to design the measuring instrument. The measuring instrument in the form of a closed-ended questionnaire was used for data collection. The data were analysed quantitatively and the results reported in the data analysis chapter. The findings of the study were then discussed, and implications made in relation to theory and practice based on which the final framework was deduced. The research design followed by this study is shown in Figure 3.1.

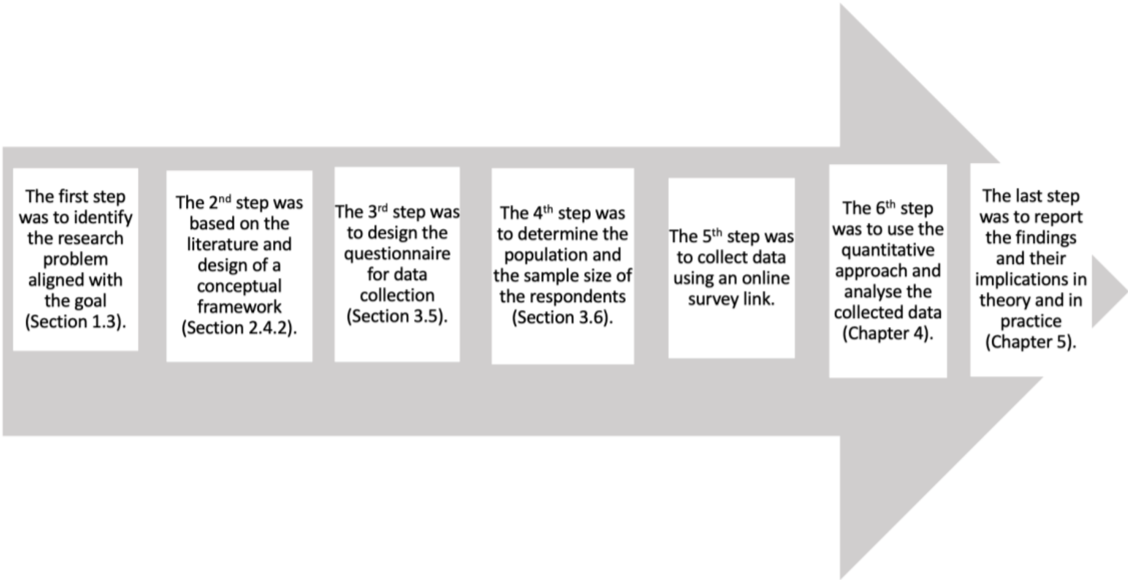

Figure 3.1: Research design

3.2 Research Paradigm

A research paradigm is defined as the researcher's view of the study being conducted. It expresses researcher's understanding of the research and helps him/her to place the study into context (Lincoln et al., 2018). A paradigm is also seen as a world view that guides research and enables a researcher to select an appropriate approach to a study being conducted (Creswell & Creswell, 2018). There are three commonly used research paradigms in information systems research, and these are positivism, interpretivism also known as constructivism and pragmatism (Yin, 2014).

This study followed the positivism paradigm since it intends to analyse the perceptions rather than feelings of respondents to come up with influential factors that can be used to develop a framework for BDA adoption. This implies that the study is objective rather than subjective and all the conclusions and discussions are based on the results from the analysed data without the involvement of the researcher's interpretations.

3.3 Research approach

The research approach is the way how a particular research is conducted, including collection and analysis of data, techniques and methods for determining population and sample sizes for the study, as well as the strategies used to reach the participants or respondents of the study (Yin, 2014). Three basic approaches are normally used in academic research, and these are quantitative, qualitative, and mixed method, though of recent design science approach has been added as an independent approach (Deng & Ji, 2018).

For this study, a quantitative approach was followed due to the fact that this study intended to analyse the patterns of respondent's perceptions that lead to the identification of factors needed for the development of the BDA adoption framework. More still, as also noted by Vachkova et al. (2023) the quantitative approach is appropriate for testing hypothesis and theories and examining the relationship between various factors. This implies that following the quantitative approach was instrumental in testing and proving the hypotheses developed in section 2.

For this study, gathering data from a large sample was possible by using quantitative research. This method was cost effective in that the organisation from which data were collected and respondents did not incur any cost by participating in this research. Respondents were only requested to set aside a couple of minutes to complete the survey questionnaire. Another advantage of this approach was that the survey was administered without the researcher having to spend time at the organisation. Analysing data statistically helps to ease interpretation of findings, making prediction for future occurrences possible with a quantitative approach. The numerical data gathered using this method made it easier to compare groups and determine the degree of agreement or disagreement among respondents based on which patterns were easy to be deduced from the respondent's answers.

3.4 Research strategy

A research strategy is a way by which a researcher reaches out to the intended participants of the study (Salkind, 2017). This study used the survey strategy whereby a close-ended questionnaire was designed and distributed using an online link that was developed using Qualtrics. At the organisation where data was to be collected, the researcher requested the contact person to send out the link to the targeted population in the organisation using simple random sampling. Being online, before simple random sampling was used to send out the link, an inclusive criteria were set that assisted the contact person to distribute the link. The inclusive criteria were that the recipient of the link should be an employee in one of the following departments, information technology department, marketing department, risk management department, compliance department, credit department, and rewards department.

The survey strategy was sought to be appropriate for this study since data were expected to be collected from a wider sample of respondents. It allowed for participants to remain anonymous and readily share their thoughts and experiences. The survey strategy allowed for simpler data gathering and analysis using statistical techniques and did away with the researcher's subjectivity. The online survey results were received in formats that could be read by data analysis software like SPSS.

3.5 Data collection methods

Data for this study was collected using a questionnaire with close-ended questions. The questionnaire was designed based on the conceptual framework whereby the constructs and sub-constructs of the framework formed the sections of the questionnaire, and their attributes were used to formulate the questionnaire items. The questionnaire was designed based on 5-point Likert scale whereby 1 and 5 represent Strongly agree and Strongly disagree respectively, 3 representing Neutral, whereas 2 and 4 will be respective intermediate values. The questionnaire also had a section for reporting the respondents' demographics.

The designed questionnaire was then transcribed into Qualtrics to formulate an online survey whose link was sent to the respondents by the contact person of the organisation using the mailing lists. Respondents were asked to fill the questionnaire and click the submission button on completion. The field questionnaire was then captured into the Qualtrics database, and the datasets were transcribed into the Statistical Package for the Social Sciences (SPSS v 25) for analysis.

3.5.1 Questionnaire coding

According to Saldaña (2016), unlike in qualitative research where coding represents specific meanings, in quantitative research coding is done to avoid crowdness and ambiguity. Hence, coding in quantitative research is only done to shorten the names of the constructs and their measuring items. In this study the constructs were coded by abbreviating their names. After receiving the filled datasets from Qualtrics, the data was exported to SPSSv25 for analysis. The constructs and their attributes were coded as follows;

- Technology characteristics was coded as TCH and its four measuring items as TCH1 to TCH4.
- Users perception of technology was coded as UPT and its three measuring items as UPT1 to UPT3.
- Top management support was coded as TMS and its four measuring items as TMS1 to TMS4.
- Size and structure was coded as SS and its three measuring items as SS1 to SS3.
- Environmental factors was coded as ENVF and its three measuring items as ENVF1 to ENVF2.
- Individual characteristics was coded as INDCH and its four measuring items as INDCH1 to INDCH4.
- Big data characteristics was coded as BDCH and its five measuring items BDCH1 and BDCH5.

- Big data analytics adoption was coded as BDAA and its four measuring items BDAA1 and BDAA4.

3.6 Population and sampling of respondents

This section describes the proposed population of the study in which the targeted informants were identified based on whom a required sample size was determined.

3.6.1 Population

Population refers to a group of people about which broad generalisations will be applied (Rahman et al., 2022). The targeted population of this study were employees in a financial institution in Gauteng Province of South Africa. Only employees based in the head office of this financial institution were targeted. From this financial institution the targeted groups were information-technology department, marketing department, risk-management department, compliance department, credit department, and rewards department.

The pre-exploratory study conducted indicated that in the targeted financial institution these departments had the following listed number of employees. Information-technology department-45, marketing-40, risk-management department-30, compliance department-30, credit department-35 and rewards department-10. This made a total population of the study to be 190.

3.6.2 Sample and sampling method

Rahman et al. (2022) define a sample as a subset of the population. In research, sampling is conducted to give meaningful representation of respondents that are to participate in a study without biasness. This study being quantitative, the sample size was obtained statistically by using the Krejcie and Morgan (1970) tool of computing sample sizes of finite population. The sample size corresponding to the population of 190 was 127. The Krejcie and Morgan (1970) tool is as illustrated in Table 3.1.

Table 3.1: Determination of sample size

N	*S*	*N*	*S*	*N*	*S*
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Note.—*N* is population size.
S is sample size.

Source: *Krejcie & Morgan (1970)*

The sample size of 127 was deemed appropriate based on that the study had to be completed within a specific time period which this sample size allowed for. After computing the sample size, simple random sampling was used to send the survey link to the respondents basing on the set inclusive criteria. Simple random sampling was used because it allowed every member of the population an equal chance of being selected and the randomisation process reduced selection bias because it ensured the sample was representative of the whole population. In addition, for this study simple random sampling was straightforward to implement because it entailed sending survey links to prospective respondents based on the inclusive set criteria. At inception of this study, it had been anticipated that the population of the study would come from three financial institutions. However, only one organisation gave permission to this study. The respondents had to be employees working in the information-technology department, marketing department, risk-management department, compliance department, credit department and rewards department.

3.6.3 Procedure for data collection

When transcribing the questionnaire into Qualtrics a 'submit button' was included so that on completion of filling the questionnaire the respondents could just click on this button and the dataset get captured in Qualtrics database. This helped to ease the process of returning the answered questionnaire and to protect the anonymity and privacy of the respondents. Answers to survey questions can often be guided by what is perceived as being socially acceptable. To mitigate against social desirability bias, the prospective respondents were informed that the survey was confidential and anonymous, and these were guaranteed by participants not needing to enter their names on the questionnaire.

3.6.4 Questionnaire link distribution

A Qualtrics link was sent to the contact person in the organisation who then distributed it to the respondents using their e-mails based on the inclusive set criteria and simple random sampling. In total, 130 survey links were sent out to prospective respondents. To mitigate against nonresponse bias, reminder e-mails were sent to the prospective respondents three weeks after the first contact. Of these, 90 completed questionnaires were captured back on the database giving a response rate of 69%. However, 22 of these were incomplete and thus were removed from the sample resulting in a usable sample of 68.

3.7 Data analysis

The collected data for this study was statistically analysed. The captured data set in Qualtrics was exported to Statistical Package for Social Sciences for analysis. However, before the data was exported to SPSS, the questionnaire and its attributes were coded to allow easy analysis and interpretation. After coding both descriptive and inferential statistics like correlation and regression were used to analyse the data. More still, the consistency table demonstrated in Table 3.2 was also used to give highlights of the flow of the analysis and how the set research objectives could be met.

Table 3.2: Consistency table

RO #	Research Objective	Hypothesis #	Hypothesis	Data collection detail	Data analysis method
1	To determine the factors influencing the adoption of big data analytics	H1 H1a H1b	Technological factors influence the adoption of BDA. Technological characteristics influence BDA adoption in financial institutions. Users perception towards technology influence BDA adoption in financial institutions.	Literature review Questionnaire Likert scale 5	Quantitative, correlation and regression
1		H2	Organisational factors influence the adoption of BDA.	Literature review Questionnaire Likert scale 5	Quantitative, correlation and regression

RO #	Research Objective	Hypothesis #	Hypothesis	Data collection detail	Data analysis method
	To determine the factors influencing the adoption of big data analytics	H2a H2b	Organisational factors due to top management support influence the adoption of BDA. Organisational factors due to size and structure of the organisation influence BDA adoption in financial institutions.		
1	To determine the factors influencing the adoption of big data analytics	H3	Environmental factors influence the adoption of BDA.	Literature review Questionnaire Likert scale 5	Quantitative, correlation and regression
1	To determine the factors influencing the adoption of BD analytics	H4	Individual characteristics influence the adoption of BDA.	Literature review Questionnaire Likert scale 5	Quantitative, correlation and regression
1	To determine the factors influencing the adoption of big data analytics	H5	Big data characteristics influence the adoption of its analytics.	Literature review Questionnaire Likert scale 5	Quantitative, correlation and regression

RO #	Research Objective	Hypothesis #	Hypothesis	Data collection detail	Data analysis method
2	To determine the benefits of big data analytics within organisations			Literature review	Content analysis
3	To establish the theories needed for the adoption of BDA			Literature review of theories	Literature review
4	To use the identified factors in the development of the framework for BDA			Questionnaire Likert scale 5	Quantitative, correlation and regression

3.8 Reliability and Validity

A study is said to be meaningful if it conforms to the procedures and standards of research. This also implies that its findings should be trusted when they are applied in various situations. According to Cohen et al. (2018), the trustworthiness of a study can only be ascertained if it conforms to the reliability and validity standards.

3.8.1 Reliability

Reliability also known as internal consistence is the ability of a measuring instrument to produce similar findings when applied in other similar settings (Tamilmani et al., 2021). The reliability of scale for the constructs was assessed using Cronbach's Alpha (α), also known as Cronbach's coefficient. The overall reliability of the questionnaire was tested and found to be 0.904. Results of the overall questionnaire reliability with 36 items are presented in Table 3.3.

Table 3.3: Overall Reliability Statistics of the Measuring Instrument

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.904	.904	36

Subsequent to the evaluation of the overall questionnaire reliability, the reliabilities of independent constructs were also tested as illustrated in Table 3.4.

Table 3.4: Reliability of Independent Constructs

Reliability Statistics

Construct	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Technology Characteristics (TCH)	.701	.703	4

Users Perception of Tech (UPT)	.533	.555	3
Top Management Support (TMS)	.780	.780	4
Size and Structure (SS)	.725	.725	3
Environmental Factors (ENVF)	.645	.644	3
Individual Characteristics (INDCH)	.743	.742	4
Big Data Characteristics (BDCH)	.710	.717	5
Big Data Analytics Adoption (BDAA)	.842	.844	4

As illustrated in Table 3.4, the reliability of the independent constructs was above the acceptable threshold, indicating the suitability of all the constructs to be used for further analysis.

3.8.2 Validity

Validity is looked at as a measure of truthfulness whereby the measuring instrument is designed in such a way that it measures what it is supposed to measure (Tamilmani et al., 2021). According to Cohen et al. (2018), in quantitative research, the validity of the study is to ensure that the measuring instrument conforms to four basic parameters, namely face validity, content validity, construct validity, and criterion validity. Cohen et al. (2018) further emphasised that these four parameters are either established by expert checking or statistically. These validity measures were achieved as follows;

a) Face validity: To ensure validity in this study and to confirm the logical flow of the questionnaire in measuring BDA adoption, the supervisor proofread and made corrections to the questionnaire. Every statement's goal was evaluated to determine if it was suitable for the measuring instrument and easy to understand.

b) Content validity: According to Sürücü and Maslakci (2020), content validity is the degree to which each item in the measuring instrument accomplishes its intended purpose. To ensure content validity in this study, it meant that the measuring instrument content needed to cover items that measure the adoption of BDA. This was achieved by comparing the measurement instrument with those of previous researchers on BDA adoption.

c) Construct validity: This is the ability to deduce test results from the concept under study, hence it is the degree to which a research instrument assesses the desired construct (Heale & Twycross, 2015). The questionnaire's sections were based on the conceptual framework's constructs which were established from the literature and from the theories and models that guided this study, and the measuring items were derived from the attributes.

d) Criterion validity: According to Mellinger and Hanson (2020), a scale's criterion validity considers how closely it corresponds with an observable attribute. This study used tests that included correlation analysis to examine the relationships between each concept in order to verify this form of validity.

3.9 Ethical considerations

Data collection did not begin prior to receiving an ethics clearance certificate from Wits Business School. The participants were informed of the general purpose of the study. Further to that, a cover letter accompanying the questionnaire stated that the survey was both confidential and anonymous and these were guaranteed by participants not needing enter their names on the questionnaire. Participants were informed that participation in the study was completely voluntary and involved no risk, penalties, or benefits whether or not they participate. They were informed of the right to withdraw from partaking at any time from the study without any consequences to them, and that their data would be used only for academic research purposes and kept confidential. Socio-demographic questions were limited to gender, age, work experience, education level, and participants were not asked to share personal identifiable information. A password was used to access the platform that houses the questionnaire and responses.

3.10 Summary

This chapter covered the methods that this study used to address the research challenge. The research paradigm, approach and strategy used in this study was given in this chapter. The data gathering methods together with how the data was analysed and the population of the study were addressed. Lastly, the chapter discussed the ethical issues and how this study dealt with them.

CHAPTER 4. ANALYSIS AND PRESENTION OF RESULTS

This chapter presents the results from the analysis conducted. The chapter first presents the demographic variables of the respondents and then the inferential statistics. The chapter further describes the process of analysis that was followed and the correlation which shows the relationships between the constructs as well as the regression that shows how each construct contributes to the overall prediction of the framework. This chapter concludes by presenting the results of the tested hypotheses.

4.1 Data screening

The data that was downloaded from Qualtrics had 90 responses, of these, 22 datasets were incomplete and thus, were discarded. Thus, the final datasets of 68 responses were used for analysis. There were no missing values for the retained 68 responses, therefore there was no need for data imputation.

4.2 Demographics

a) Gender

The results presented in Figure 4.1 show that there was a slight majority of males in the sample, comprising 54% (n = 37) of the sample, while females make up 46% (n = 31) of the sample. Other researchers such as Venkatesh et al. (2012) have determined that the demographic factor of gender is important for the acceptance, adoption, and use of technology. According to the findings, the survey was completed by more males than females. This gender split correlates with the share of the employed population in South Africa which was higher among men than women.

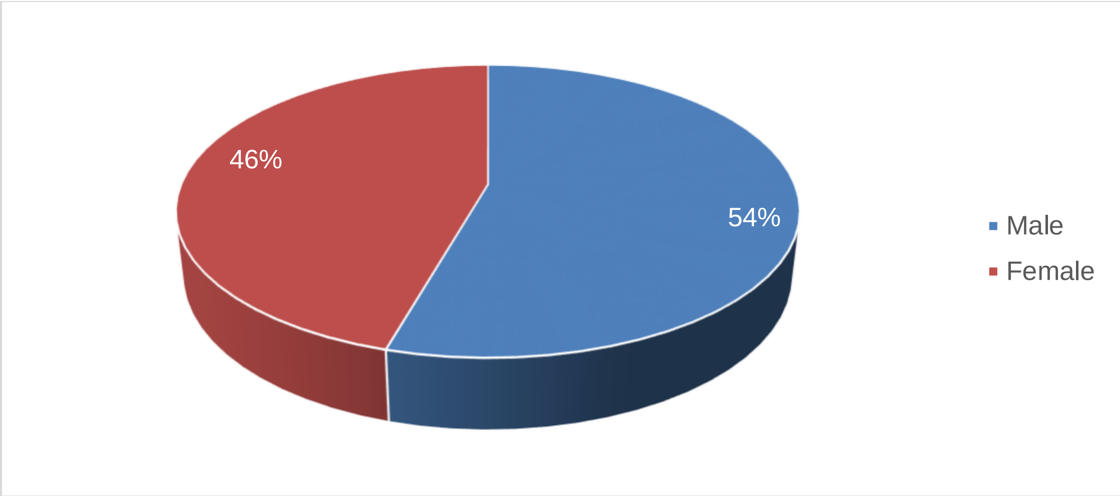

Figure 4.1: Respondents by gender

b) Age

The age distribution within the sample was 6% (n = 4) being between 18 and 27 years old, 53% (n = 36) were aged between 28 and 37 years, 37% (n = 25) fell within the age range of 38 to 47 years, 3% (n = 2) were aged between 48 and 57 years, and only 1% (n = 1) were 58 years and above. Researchers such as Venkatesh et al. (2012) have discovered that age is a good demographic indicator for predicting the adoption and use of technical innovations. This suggests that mature individuals are more responsible in terms of BDA adoption. Given that 94% (n = 64) of the respondents were above 28, it can be assumed that those who answered the questionnaire were seen to be more responsible within the financial institution. Results are as illustrated in Figure 4.2.

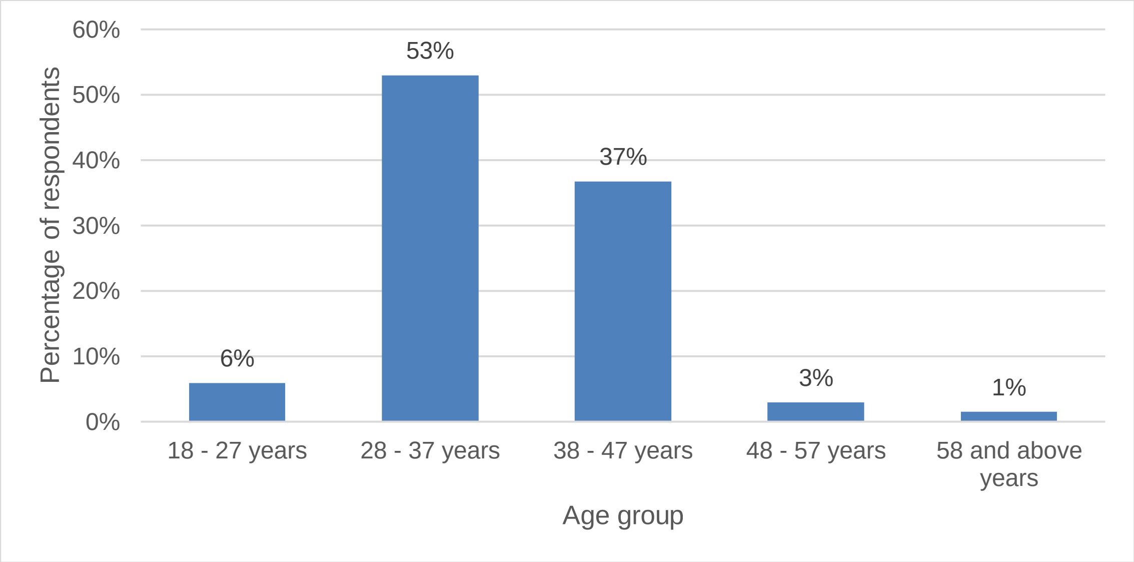

Figure 4.2: Respondents by age

c) Level of education

Results illustrated in Figure 4.3 show that the highest attained level of education within the sample was distributed as 6% (n = 4) having completed Grade 12 and below education, 10% (n = 7) held diplomas, 35% (n = 24) had attained degrees, advanced diplomas, or BTech qualifications, 32% (n = 22) had completed honours or postgraduate diploma programs, while 16% (n = 11) had achieved masters or PhD degrees. These results show that the study's findings can be confidently presented because the majority of respondents have degrees or higher qualifications. A high degree of education improves the findings' content and criterion validity since it has been shown in other studies to be significant for decision-making (Rahim et al., 2022).

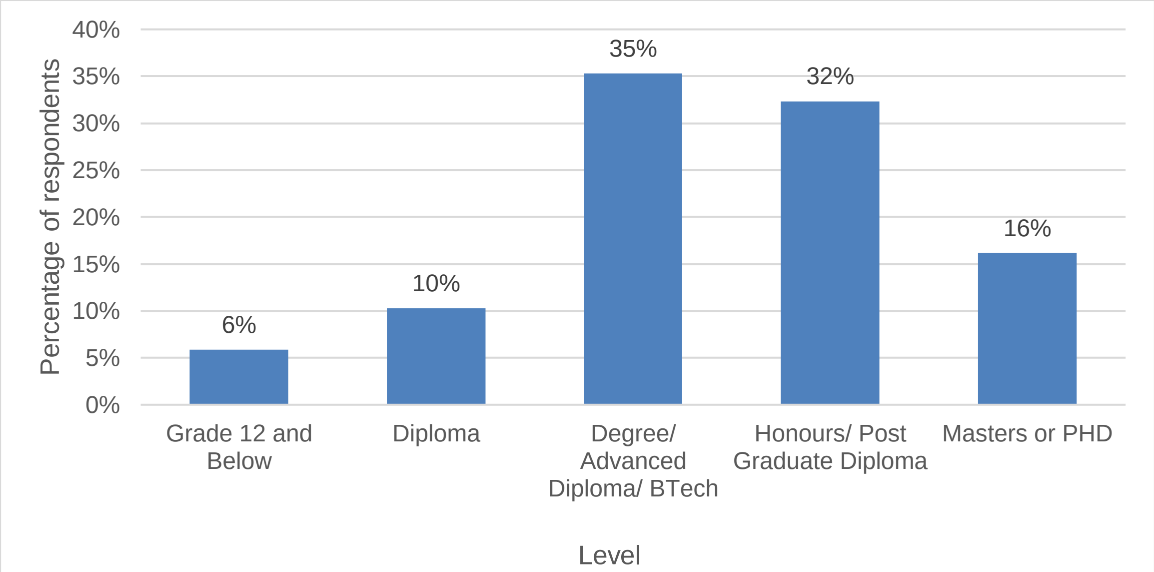

Figure 4.3: Respondents by highest level of education

d) Work experience

The distribution of participants' professional experience levels was examined. It can be noted from Figure 4.4 that 9% (n = 6) of respondents possessed between 0 to 5 years of experience in their respective fields. A proportion of 22% (n = 15) of participants reported having accumulated 6 to 10 years of experience. Notably, a substantial proportion, constituting 38% (n = 26) of the sample, had an experience range of 11 to 15 years. Additionally, 24% (n = 16) of participants had accrued 16 to 20 years of experience. A smaller subset of individuals, comprising 6% (n = 4), reported an experience range of 21 to 25 years, demonstrating a select group with extensive professional backgrounds. Lastly, only 1% (n = 1) of respondents had 26 or more years of experience, representing a minority within the sample possessing an exceptionally high level of tenure and expertise.

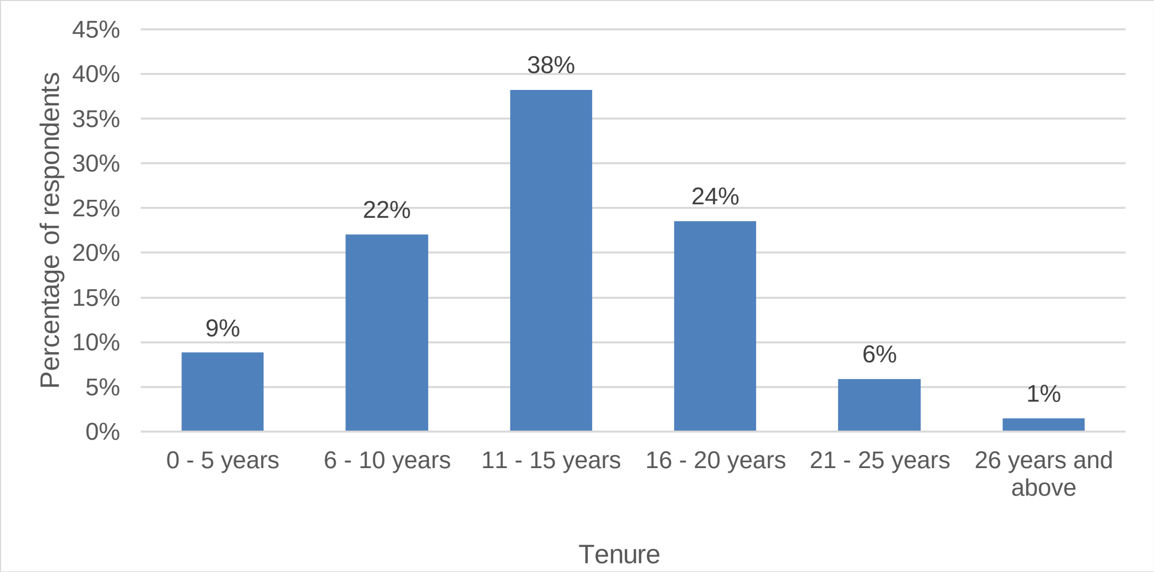

Figure 4.4: Respondents by working experience

e) Department

The sample was represented by participants that were predominantly from the marketing departments, comprising 57% (n = 39) of the sample. Following marketing, the IT department was the next most represented, constituting 25% (n = 17) of participants. Additionally, a smaller proportion of individuals were affiliated with risk management, compliance, and credit departments, each comprising 6% (n = 4) of the sample. This distribution highlights the diverse representation of various departments providing insight into the breadth of expertise and perspectives captured for this study. The results are presented in Figure 4.5.

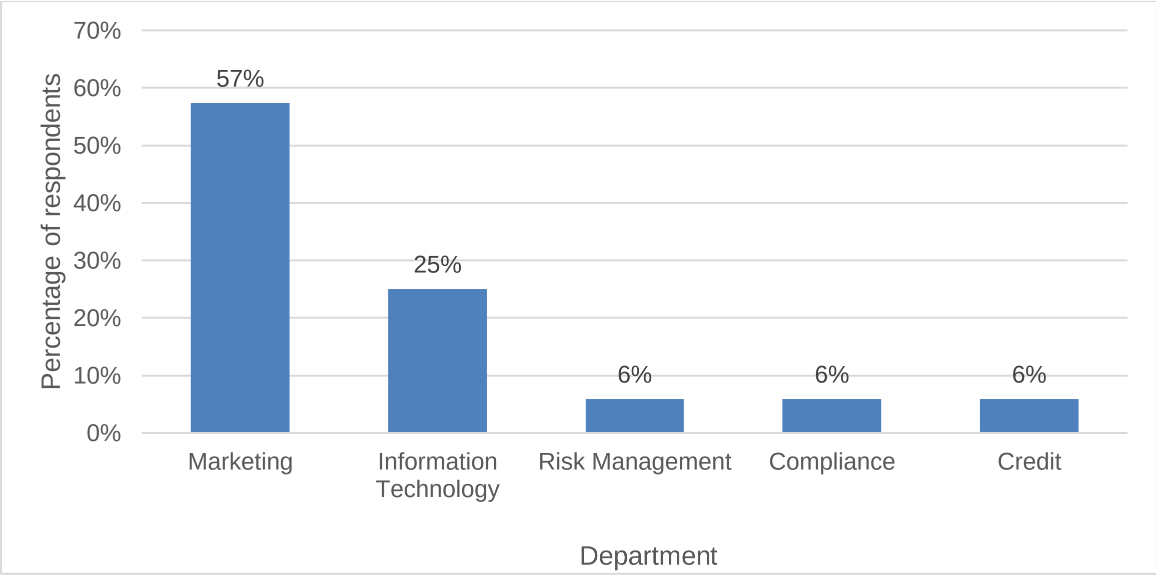

Figure 4.5: Respondents by department

4.3 Pearson's correlation of the constructs

Correlation coefficients provide an indication of the strength of the relationship among two variables and values can range from -1 to 1, with -1 depicting a negative relationship and 1 depicting a positive relationship. (Schober et al., 2018). According to Obilor and Amadi (2018), Pearson's coefficient has emerged as the most popular metric for characterising the strength of the relationship between two variables based on the assumptions that:

a) Two variables have a linear relationship with one another,

b) There should be an approximate normal distribution of the data and

c) There is a causal relationship between the two variables.

The Pearson's correlation technique was used in this study to represent the correlation between the constructs as indicated in Table 4.1.

Table 4.1: Correlation of Constructs

Correlations

		TCH	UPT	TMS	SS	ENVF	INDCH	BDCH	PBDAA
	Pearson Corr.	1							
TCH	Sig. (2-tailed)								
	N	85							
	Pearson Corr.	.413*	1						
UPT	Sig. (2-tailed)	.000							
	N	85	85						
	Pearson Corr.	.549**	.446**	1					
TMS	Sig. (2-tailed)	.000	.000						
	N	85	85	85					
	Pearson Corr.	.473*	.542**	.777	1				
SS	Sig. (2-tailed)	.000	.000	.000					
	N	85	85	85	85				
	Pearson Corr.	.456**	.375**	.664**	.683	1			
ENVF	Sig. (2-tailed)	.000	.000	.000	.000				
	N	85	85	85	85	85			
	Pearson Corr.	.433**	.628**	.609	.652	.555**	1		
INDCH	Sig. (2-tailed)	.000	.000	.000	.000	.000			
	N	85	85	85	85	85	85		
	Pearson Corr.	.383*	.361**	.321**	.375**	.464**	.412*	1	
BDCH	Sig. (2-tailed)	.000	.001	.003	.000	.000	.000		
	N	85	85	85	85	85	85	85	
	Pearson Corr.	.506**	.605	.391**	.499**	.395**	.549	.388*	1
BDAA	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	
	N	85	85	85	85	85	85	85	85

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The findings shown in Table 4.1 indicate that the most closely correlated variables are size and structure (SS) and top management support (TMS), with a p-value of .664 at the 0.01 level of significance. The environmental factors (ENVF) and size and structure (SS) came in second with a p-value of .652. Thirdly the environmental factors (ENVF) and user's perception of technology (UPT) with a p-value of .628 at the 0.01 level of significance. The environmental factors

(ENVF) and top management support (TMS) were significant with a p-value of .609. Big data characteristics (BDCH) and user's perception of technology (UPT) had a correlation with a p-value of .605. Individual characteristics (INDCH) and user's perception of technology (UPT) associated with low correlation with a p-value of .361 at 0.01 level of significance. The lowest correlation was between individual characteristics (INDCH) and top management support (TMS), with a p-value of .321 at 0.01 level of significance.

4.4 Regression of the Constructs

Regression is statistical technique used to simulate and analyse the relationship between variables and determine how each one affects the model's forecast (Tranmer & Elliot, 2008). The main objective of regression analysis is to examine the relationship between one or more independent variables and a dependent variable. Table 4.2 presents the overall prediction of the model for BDA adoption in South African financial institutions.

Table 4.2: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Est.	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.708[a]	.501	.444	.62434	.501	10.576	7	77	.000

a. Predictors: (Constant), BDCH, TMS, UPT, TCH, ENVF, INDCH, SS

The model summary presented in Table 4.2 shows that the overall prediction of the conceptual model for the BDA adoption in South African financial institutions is 50.1% (R^2 = .501). Table 4.3. indicates the contribution of the independent variables to the overall prediction of the BDA adoption model.

Table 4.3: Regression Coefficients[a] of Constructs

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.536	.064		8,375	.000		
	TCH	.351	.131	.275	2.685	.009	.629	1.589
	UPT	.426	.141	.332	3.012	.004	.545	1.836
	TMS	.238	.054	.398	4.375	.000	.520	1.923
	SS	.212	.167	.178	1.266	.209	.300	3.333
	ENVF	.016	.150	.013	.105	.916	.433	2.310
	INDCH	.228	.114	.190	1.997	.041	.428	2.336
	BDCH	.104	.053	.185	1.977	.044	.706	1.417

a. Dependent Variable: BDAA

Results illustrated in Table 4.3 indicate that, with the exception of size and structure and environmental factors, most of the constructs show a significant contribution to the adoption of BDA in financial institutions. Top management support had the highest contribution with a prediction power of 39.8% ($\beta = .398$) at $p = .000$; this was followed by user's perception of technology with a prediction power of 33.2% ($\beta = .332$) at $p = .004$, and users perception of technology with a prediction power of 27.5% ($\beta = .275$) at $p = .009$. Due to the highly significant correlation values, the results featured the examination of the Variance of Inflation Factor (VIF) which was used to establish whether multicollinearity existed. A moderate degree of correlation exists between the variables if the VIF value is 1< VIF < 5 and if the VIF value is greater than 10 it shows the existence of multicollinearity (Shrestha, 2020). As indicated in Table 4.3, multicollinearity does not exist as all the VIF values were less than 5.

4.5 Testing the Hypotheses

According to Cohen et al. (2018), a significance level of 0.05 is considered appropriate. Regression analysis was performed to assess the set of hypotheses by establishing a link between the variables with a high contributing power to the prediction of the model by significantly influencing the dependant variable. The results are shown in Table 4.5. Both technology and organisational factors had to be regressed with the dependent variable by running the t-test as indicated in Table 4.4.

Table 4.4: Regression Coefficients[a] of Technological and Organisational Factors

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	.207	.038		5.415	.001			
	TECHF	.916	.162	.602	5.639	.000	.661	.529	.465
	ORGF	.113	.132	.092	.858	.393	.474	.094	.071

a. Dependent Variable: BDAA

As demonstrated in Table 4.5, out of the nine hypothesized relationships, six were accepted while three were rejected. The rejected hypotheses are the influence of organisational factors, organisational factors due to size and structure and environmental factors to BDA.

Table 4.5: Testing the Hypotheses

Suggested Hypothesis	Results Obtained	Action
H1: Technological factors (TECHF) influence the adoption of BDA.	P = .000 < .05	Supported
H1a: Technological characteristics (TCH) influence BDA adoption in financial institutions	P = .009 < .05	Supported
H1b: Users perception towards technology influence BDA adoption in financial institutions	P = .004 < .05	Supported
H2: Organisational factors (ORGF) influence the adoption of BDA	P = .393 > .05	Not supported
H2a: Organisational factors due to top management support (TMS) influence the adoption of BDA	P = .000 < .05	Supported
H2b: Organisational factors due to size and structure (SS) of the organisation influence BDA adoption in financial institutions	P = .209 > .05	Not supported
H3: Environmental factors (ENVF) influence the adoption of BDA	P = .916 > .05	Not supported
H4: Individual characteristics (INDCH) influence the adoption of BDA	P = .041 < .05	Supported
H5: Big data characteristics influence the adoption of its analytics	P = .044 < .05	Supported

4.6 Summary

In this chapter the findings of the study were presented. The chapter began with presenting the demographic variables of the respondents which included gender, age, level of education, work experience, and department. The chapter present correlation analysis followed by regression analysis to simulate and analyse the relationship between variables. The chapter concluded by presenting the results of the tested hypotheses. In the following chapter the results of the study are discussed as well as the limitations and recommendations for future research.

CHAPTER 5. DICUSSION, CONCLUSION AND RECOMMENDATION

The discussion of the results of the study is covered in this chapter. This discussion is done along with the interpretation of the findings and their implications to theory and practice. Further still, the chapter discusses the findings in relation to the research goals and objectives of the study. The results are analysed considering the study's hypotheses and their implications for theory and practice. The chapter also highlights the limitations of the study. The chapter gives the limitations and recommendations as well as guidelines for future research.

5.1 Overview of the study

The goal of the study was to develop a framework for the adoption of BDA in South African financial institutions. It is without doubt that operations in financial institutions generate a lot of data that need to be transformed into valuable business information. In order to make sense out of the data that they receive and generate from a variety of sources in different formats, financial institutions are acquiring and using BDA tools (Bansal et al., 2022).

In order to accomplish the goal of the study, particular objectives were set to be achieved. These included determining the factors influencing the adoption of BDA, exploring the benefits of BDA within organisations, establishing the theories needed for the adoption of BDA, and using the identified factors in the development of the framework for BDA adoption. The study also examined previous research on BDA adoption which helped in selecting the theory and methodology that was used.

5.1.1 Lessons learn from the study

In recent years there has been a growth in disruptive technologies and among them cloud technology, advanced analytics, machine learning and artificial intelligence to mention a few. Different types of businesses have been impacted by the 4IR technologies and many are realising the benefits of BDA hence the increase in the need for better analytics. According to El-Haddadeh et al. (2021), BDA capabilities offer organisations the opportunity to make more informed business decisions and boost overall company performance. Vassakis et al. (2018) noted that unstructured data is expanding faster than structured data, consequently, new kinds of processing abilities are required to get data insights that enhance decision-making. Operations in financial institutions generate a lot of data resulting in a need to analysing it and turning it to valuable business information. Big data analytics is a way of attaining value from these large volumes of data. Matsepe and Van der Lingen (2022) observed that fewer frameworks have been developed to guide the adoption of BDA and those available are not contextualised for financial institutions in South Africa.

Many organisations still need to investigate the benefits of BD, assess their organisational preparedness, and acquire the necessary technology. Therefore, it is imperative to investigate the mechanisms and associated dynamics of BDA adoption by organisations, a task that calls for additional research (El-Haddadeh et al., 2021). The results of the study demonstrated that technological factors are very important in the development of the BDA adoption framework. This implies that organisations should develop integration processes to enable the effective implementation of BDA. Furthermore, organisations should highlight the benefits that will be derived from adopting BDA to get buy-in from the users within the organisation.

El-Haddadeh et al. (2021) observed that establishing a culture of analytics at the highest level of an organisation is essential to its success. The results of the study demonstrated that organisational factors due to top management support are very important in the development of the BDA adoption framework. This implies that senior management must provide the required direction and endorse programmes pertaining to integration of new technologies. Organisations need to set aside enough budgets and personnel to implement BDA successfully. A lack of employees with correct data analytics skills is often a challenge and organisations should address this by training employees and recruiting employees with the relevant skills.

5.1.2 Relevancy of the methodology used for the study

This study utilised a quantitative approach for which data was gathered from several departments in one financial institution. Different users within an organisation perceive factors that lead to the adoption of BDA differently. It was necessary to include as many respondents as possible in order to create a framework that could account for all elements. From a methodological point of view, gathering data from a larger number of users was possible by using the quantitative approach. The quantitative approach was appropriate for testing hypotheses and examining the relationship between various factors (Vachkova et al., 2023). In order to measure the associations between the constructs, statistical methods such as regression analysis and correlation analysis were required. Had a quantitative approach not been followed, it would have been difficult to conduct such tests suggesting that the methodology used for this study was relevant.

5.2 Discussion and interpretation of findings

This section presents the discussion of the results of the study and gives the interpretations of the findings in relation to theory and practice. In this section, the discussion in relation to study goal and objectives is given followed by that of the hypothesized relationships of the constructs.

5.2.1 Discussion of the objectives and goal of the study

The goal of the study was to develop a framework for the adoption of BDA in South African financial institutions. The objectives were:

1. To determine the factors influencing the adoption of BDA
2. To explore the benefits of BDA within organisations
3. To establish the theories needed for the adoption of BDA
4. To use the identified factors in the development of the framework for BDA

a) Discussion of the findings in respect to the first objective

The first objective was to determine the factors influencing the adoption of BDA. A review of the literature was conducted to achieve this objective drawing from a range of BDA adoption studies. This study dedicated Section 2.2.3 to discussing the factors influencing the adoption of BDA. The identified factors were also presented in Table 2.1. The literature shows that there are many factors that play a role in BDA adoption in organisations. Additional factors were identified in the related work that was covered in Section 2.3. According to the literature technological factors include compatibility, privacy and security, perceived benefits, complexity and reliability; organisational factors include supporting of IT budgets, training, human resources expertise, organisational culture, communication and policies and standards; and environmental factors include competitive pressure, vendor support and regulations and laws. Further still, according to the literature individual characteristics include attitude, skills, beliefs and learnability; and BD characteristics include volume, velocity, variety, veracity and value. On testing the hypotheses, factors namely, technological factors, organisational factors due to top management support, individual characteristics and BD characteristics were found to significantly influence the BDA adoption framework.

b) Discussion of the findings in respect to the second objective

The second objective of the study was to explore the benefits of BDA within organisations. As shown in Section 2.1.2, literature on benefits of BDA was reviewed in order to accomplish this goal. As stated by Raguseo (2018), typical benefits of BDA can be categorised as transactional, strategic, transformational and informational. In addition, BDA enables organisations to make improvements in data management and have simpler access to data. Using BDA organisations can receive real-time information and examine customer reviews and sentiment analysis which allows them to improve their performance and enhance customer service. It is possible to establish useful connections with other organisations through BDA, for instance financial institutions depend on data from credit bureaus to assess the credit worthiness of customers. Through integrating and coordinating data from multiple sources BDA plays an important role in the different phases of crisis management allowing organisations to respond effectively to situations (AL-Ma'aitah, 2020). More still, several uses and benefits of BDA within financial institutions were discussed as demonstrated in Section 2.2.1. There are several benefits of BDA in financial institutions such as customer acquisition and retention, fraud detection, customer segmentation, personalisation and risk management (Abraham et al., 2019; Hasan et al., 2021). Using BDA, financial institutions can gain deeper insights into the behaviours of customers and more effectively segment and target customers with personalised offers.

c) Discussion of the findings in respect to the third objective

The third objective was to establish the theories needed for the adoption of BDA. The BDA adoption theories were identified from the literature. The most commonly used theories and frameworks in BDA adoption research are Dynamic Capabilities (DC), Resource-Based View (RBV), Technology Acceptance Model (TAM), Diffusion of Innovation (DOI), and Technology-Organisation-Environment Framework (TOE) (Aboelmaged & Mouakket, 2020). From the aforementioned frameworks, this study used TOE as its underpinning theory since it was capable of working as a shell to accommodate the identified factors in the literature that influence BDA adoption. The TOE theory has been used to explain the adoption and use of technology within organisations since it allows the accommodation of various factors that influence the adoption and use of technology (Maroufkhani et al., 2023).

d) Discussion of the findings in respect to the fourth objective

The fourth objective was to use the identified factors in the development of the framework for BDA adoption in financial institutions. The identified factors in the literature were used to design the framework for BDA adoption in financial institutions. The constructs featured were technology, organisation, environment, which are more closely connected to the TOE framework, individual characteristics, and BD characteristics to inform the development of the conceptual framework that is demonstrated in Figure 2.2. A measuring instrument was developed based on this conceptual framework to gather data that was analysed quantitatively. Linear regression analysis was used to test the hypothesised relationships as illustrated in Table 4.3 and Table 4.4. The results of the regression analysis presented the beta (β)-values which ranked the factors according to their contribution to the overall prediction of the framework. The final framework for BDA adoption was designed based on the results of the tested hypotheses.

e) Discussion and implications of the findings in relation to the goal

The goal of this study was to develop a framework for the adoption of BDA in South African financial institutions. To accomplish this goal, a section of the literature on the factors was covered in section 2.4 and a conceptual framework was developed as illustrated in Figure 2.2. Based on this, some hypotheses were developed. Not all of the identified factors contributed significantly as illustrated in the regression model in Table 4.3 and Table 4.4, and the results of the tested hypotheses shown in Table 4.5. As a result, not all the factors were included in the final framework shown in Figure 5.1.

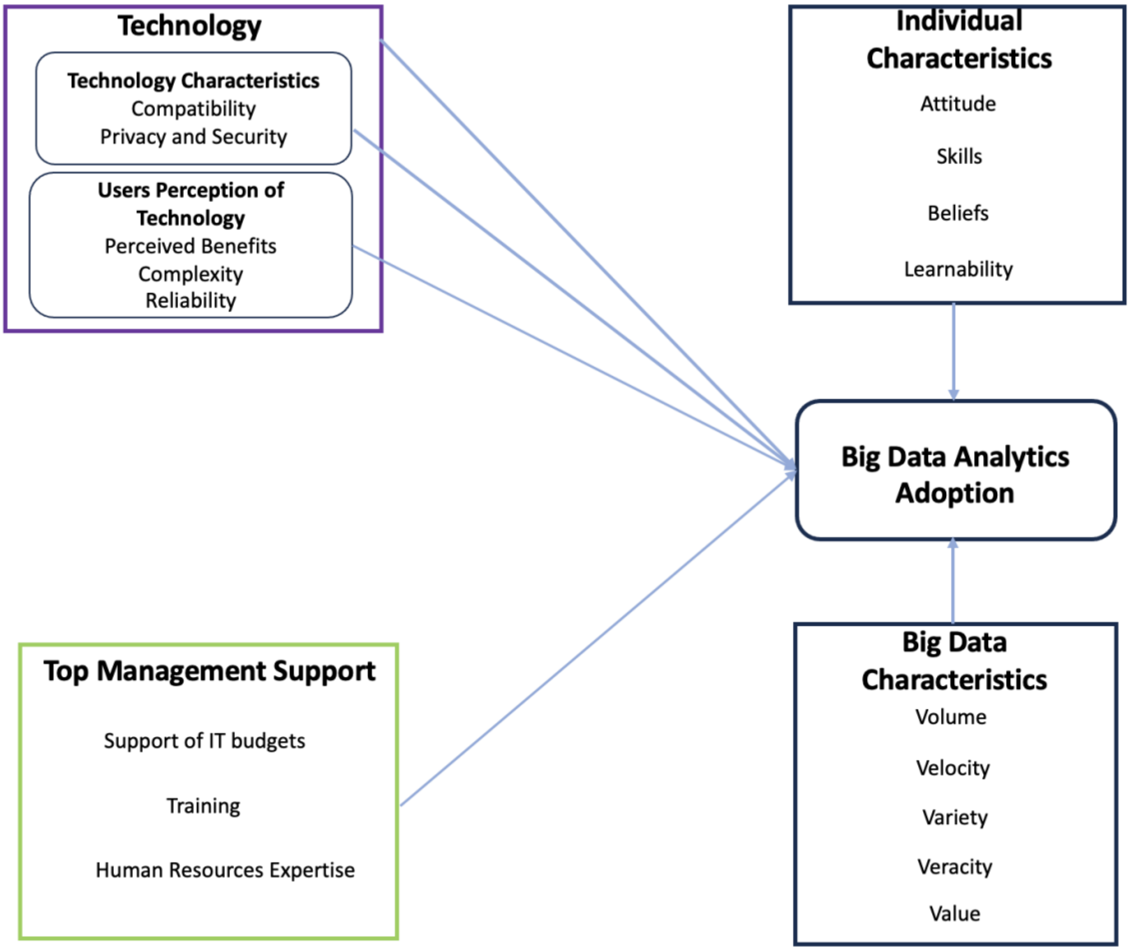

Figure 5.1: Big Data Analytics Adoption Framework

5.3 Discussion and interpretations of the Hypotheses

The hypotheses for this study were tested at 0.05 level using the p-value. Not all the hypotheses that were tested were found to be significant. This section discusses the tested hypotheses' results and how they affect theory and practice.

H1: Technological factors influence the adoption of BDA. This hypothesis was ***accepted***. The results of this study demonstrate the significance of technological factors in the development of the BDA adoption framework. This means the success and efficacy of deploying BDA solutions within organisations is significantly influenced by technological factors. The findings of this study are consistent with those of previous research (Al-Dmour et al., 2023; Maroufkhani et al., 2020b). Evolving technologically is very important for organisations especially if that will assist in differentiating themselves from competitors, serve customers better and grow. Furthermore, it is mentioned that managing massive data volumes, enabling sophisticated analytics algorithms, and guaranteeing the effective processing and storing of data necessary for analytics projects all depend on the existence of a strong and scalable IT infrastructure (Horani et al., 2023).

H1a: Technological characteristics influence BDA adoption in financial institutions. This hypothesis was ***accepted***. This finding implies that technological aspects such as compatibility and privacy and security play an important role in BDA adoption. The findings of this study concur with those of previous researchers such as Sekli and De La Vega (2022) who found that compatibility has a significant impact on BDA adoption. The extent of compatibility depends on what is required to integrate to other systems, and the easier it is the higher the chances of adopting other IT technologies. The significant effect of compatibility on BDA adoption contrasts with the findings of Maroufkhani et al. (2020a). Compatibility has more of an impact on financial institutions decisions to embrace BDA in comparison to SME's as compatibility between existing procedures is a key consideration when making decisions. Privacy and security are important in financial institutions especially because the data they handle contains sensitive information and needs to be kept securely. These findings are also in agreement with Horani et al. (2023), who found that when handling sensitive data, security and privacy considerations are very important. Attackers can gain unauthorised access to the technological infrastructure, if there are any weaknesses, and tamper with all information within organisations' databases. In determining whether or not new technology is adopted, security and privacy play a crucial role. This means that information security should always be a top priority for financial institutions and organisations should create awareness among employees around the importance of data security.

H1b: Users perception towards technology influence BDA adoption in financial institutions. This hypothesis was ***accepted***. This finding is consistent with El-Haddadeh et al. (2021), who found that there was a positive relationship between perceived benefits and BDA adoption. Organisations must consider the advantages of a technology before adopting it, if they believe analysing data in real-time will add value to customer experience and decision making there is likelihood of BDA adoption. The perceived benefits may encourage and motivate organisations to adopt new technology (Wahab et al., 2021). According to Lai et al. (2018), in a highly competitive environment organisations must evaluate the advantages of new technologies before adopting them.

The acceptance of this hypothesis means that technology that is easy to use will encourage organisations to use and implement it, this is agreement with Al-Dmour et al. (2023) who stated that leaders and experts should select BD solutions that are simple to set up and operate. This study contends that an organisation would be highly likely to use and embrace BDA if it believes that its adoption would be easy and compatible with its existing systems. In addition to being easy to implement, systems should be able to perform the functions for which they were designed as there are high expectations for performance and functionality.

H2: Organisational factors influence the adoption of BDA. This hypothesis was ***not accepted***. This finding means that organisational factors do not have an influence in BDA adoption in financial institutions. This finding is contrary to that of Walker and Brown (2019) who indicated that organisational elements influence the adoption of BDA and Maroufkhani et al. (2020b) who found that the organisational context has a significant positive effect on BDA adoption. The finding, furthermore, contradicts what Al-Dmour et al. (2023) alluded to that the most significant predictor of technology use by banks are organisational aspects. The implication of this finding is that in determining the adoption of BDA within the organisation other factors, such as technological factors and top management support, are at play.

H2a: Organisational factors due to top management support influence the adoption of BDA. This hypothesis was ***accepted***. The finding is in alignment with that of Lufti et al. (2022), who suggested that senior management needs to find qualified BD vendors, hire staff with the right expertise, and provide current staff with the required training, as well as set aside funds for BDA implementation. The availability of internal resources within an organisation with BDA expertise enhances its analytical strength by simplifying the process of comprehending data sources and maximising their potential for business development and it is beneficial for organisations in the long term to employ and train staff compared to outsourcing (Behl et al., 2019). Top management provide the funding and without their support it might be difficult to get the required resources for technology adoption. Top management support has a key role in adoption of different types of technologies and they should create a conducive environment for successful adoption. This finding is also in agreement with that of Matsepe and Elma van der Lingen (2022) who noted that to receive funding and convince other top leaders of the necessity of innovation, it was important to have advocates for innovation at top management level. According to Lai et al. (2018), if top management recognise the benefits that BDA can provide, they are willing to contribute to BDA capability via human resources expertise and sufficient financial or administrative support. These findings mean that organisations with top management that is open to new IT innovations and employees with the necessary skills are highly likely to support BDA adoption.

H2b: Organisational factors due to size and structure of the organisation influence BDA adoption in financial institutions. This hypothesis was ***not accepted***. This finding supports that of Matsepe and Elma van der Lingen (2022), who found that organisation size had no effect on adoption of technology. The implication of this finding is that organisational aspects that include organisational culture, communication, polices and standards do not play a crucial role in BDA adoption. As noted by Matsepe and Elma van der Lingen (2022), established financial institutions were more conservative and had extensive regulations in place that prevented the adoption of developing 4IR technologies within these organisations. However, this is in contrast with Sekli and De La Vega (2022) who noted that clearly established policies and standards have a positive effect on technology adoption by creating suitable conditions for organisations to adopt new innovations such as BDA. A functional structure is one of the most prevalent organisational structures in traditional financial institutions and is characterised by centralised leadership, hierarchical in nature and have well-defined decision-making authority. Centralised leadership can be rigid, and slow to adapt to changing needs resulting in taking a long time to adopt new technologies.

H3: Environmental factors influence the adoption of BDA. This hypothesis was ***not accepted***. Although environmental factors have been shown to be important in some BDA adoption studies in financial institutions conducted in developing nations, this study revealed no evidence of their significance (Al-Dmour et al., 2023; Mohammad et al., 2022). This means environmental factors comprising of competitive pressure, vendor support, regulations and laws have no significant influence on BDA adoption. This finding is in agreement with Nam et al. (2019), who concluded that organisations do not accept and use innovation because of their competitors. In other words, the level of rivalry does not directly encourage organisations to adopt BDA. This study's findings support a study by Raab et al. (2024) which found that organisations in China and Netherlands regard favourable laws and regulations as the least important factor in BDA adoption. However, it makes sense that laws and regulations should safeguard data security rather than heedlessly promoting growth. Businesses may find it more difficult to use BDA if regulations are restrictive. Therefore, in order to develop effective, sensible, and adaptable regulations that meet the needs of society and evolving technologies, governments must work with academic institutions and business leaders. This finding implies that technological factors and top management support take precedence over environmental concerns when considering BDA adoption. If top management in the organisation provides strong support in the areas of budgets, training of staff, hiring qualified personnel, establishing clear service level agreements (SLAs) with vendors and compliance with regulations, these are important for BDA adoption.

H4: Individual characteristics influence the adoption of BDA. This hypothesis was ***accepted***. This finding supports that of Youssef et al. (2022), who found that staff who have more information system knowledge, expertise, and capacity are more likely to use BDA; and of Matsepe and Elma van der Lingen (2022) who concluded that adoption of technology is positively influenced by technical skills. The individual characteristics consist of attitude, skills, beliefs, and learnability of the technology users. When organisations are considering adoption of technologies, information system skills of employees are essential, and organisations should focus on upskilling their current employees. Furthermore, Yu et al. (2022) noted that managers who possess advanced analytical knowledge and abilities leverage analytics more frequently when making decisions. In addition, if individuals believe that using insights can enhance their decision-making allowing them to make better decisions, they are highly likely to adopt BDA. This finding concurs with that of Gangwar (2020), who observed that an individual possessing the necessary knowledge and skill set to use BD will be able to recognise its benefits and find it easy to use. This finding is in line with Nguyen et al. (2024), who pointed out that employees' IT expertise is essential for businesses driven by BDA to succeed.

H5: BD characteristics influence the adoption of its analytics. This hypothesis was ***accepted***. Big data characteristics were found to be significant in this study, meaning that the amount of data, the speed at which the data are supplied, the diverse range of data sources, the types of data and the insights derived from the data all influence the adoption of its analytics. This finding concurs with that of Lutfi et al. (2023), who observed that data velocity and data variety influence BDA adoption. However, in contrast BD volume was found not to have a significant effect on BDA adoption. Furthermore, the finding is supported by Ghasemaghaei (2021), who noted that organisations with the ability to gather and analyse data in real-time from various sources may be able to get more reliable and consistent data regarding particular tasks. Gathering data from numerous sources might improve value creation for organisations. However, they should ensure that they are collecting data from trustworthy sources because poor quality data might present inaccurate and misleading information. The implication of this finding is that to collect, process and clean these large amounts of data in various formats and from different sources, organisations need to have the right technology, the skills to use it and management buy-in to provide the budget.

5.4 Contribution of the study

It was found that not many studies had been done on BDA adoption in the context of South African financial institutions, and crucially, few had used the TOE framework to explain why South African financial institutions were adopting BDA. The developed framework contributes to the theoretical understanding of BDA adoption in the context of a developing economy. Furthermore, top management support was the most important factor in determining BDA adoption. This means that senior leadership in organisations play an important role in decisions pertaining to the adoption of BDA. However, organisational factors, environmental factors and organisational factors due to size and structure of the organisation were not significant compared to top management support because BDA adoption requires budgets, training of staff, hiring qualified personnel and this requires buy-in from organisation senior leadership. These findings are unique to BD related studies and add to the body of literature on BD research.

This research has some significant implications for practice and management in addition to its theoretical contributions. As can be seen from the findings of this study, technological factors are significant in the adoption of BDA. When organisations are making decisions about adopting new technologies it is essential to solicit input from different departments to ensure that the technology that is eventually acquired accommodates the needs of different users. To build a pool of internal data analytics skills, it is important for organisations to continuously train users of the BDA tools and where necessary provide resources to recruit skilled individuals. Furthermore, individuals with data analytics skills leverage analytics often in decision-making (Yu et al., 2022). Characteristics of BD were found to be important in the adoption of its analytics and this means organisations should source the appropriate technology to be able to collect and analyse all types of data.

The adoption of BDA by South African financial institutions provides many opportunities, nevertheless it also presents drawbacks with major implications for stakeholders including organisations, customers, regulatory authorities and technology companies. Adopting BDA by financial institutions necessitates rigorous compliance with international rules as well as South Africa's POPIA. The consequences for regulators will be for a greater need for effective frameworks to monitor the ethical use of customer data and working together with financial institutions to strike a balance between consumer protection and innovation. If organisations do not comply, customers may worry about the security and privacy of their data and demand that financial institutions provide safe platforms and appropriate data usage guidelines. Data quality and legacy systems are a common challenge among organisations, financial institutions may face difficulties integrating data from several legacy systems into unified analytics platforms. Technology companies must address integration gaps by providing scalable, interoperable solutions tailored to the South African market.

Availability of experts with proper skills is essential for BDA adoption, the implication for financial institutions is that adoption may be hampered by a lack of qualified data scientists and analytics specialists. In order to adjust to the evolving technological world, employees must reskill and upskill. As financial institutions implement BDA technologies, technology companies should offer them assistance and training. Financial institutions must make a large investment in software, infrastructure, and human resources expertise for successful BDA adoption and the implication for smaller financial institutions is that it could be difficult to compete with bigger, more established firms. As data volume and complexity increase, financial institutions become more vulnerable to cyberattacks and data breaches. For customers, if systems are infiltrated, there is a higher chance of financial fraud and identity theft. The associated challenges with BDA adoption in financial institutions require all the parties involved to take proactive measures to optimise benefits and minimise risks.

5.5 Limitations of the study

Like most empirical research, this study has constraints of its own that could affect how broadly the findings are applied. The sample population is the first limitation of this study. The data was collected from respondents that were employees based at head office of only one financial institution in South Africa. In addition, there are many organisations that are categorised as financial institutions whose use and application of BDA may differ. The findings of this study may lack generalisation to the other financial institutions and a thorough understanding of the domains of financial institutions. This may suggest that respondents from these various financial institutions have different viewpoints of BDA adoption, which could result in different interpretations and conclusions. Another limitation is that the results were obtained in South Africa, a developing country. In addition, the findings of this study cannot be generalised for other types of organisations and geographies. Future studies should confirm this study results in different situations. A cross-sectional data collection method was used for this study meaning that this approach limits the demonstrability of causation in the correlations between the factors. Participants' responses were limited to the options listed in the survey because of quantitative research. Future studies can use a mixed approach to get deeper insights into the subject.

5.6 Recommendation and future studies

Only data from employees in one South African financial institution was collected for this study, it cannot be generalised to other financial institutions. For future studies, it is recommended that the scope is expanded to include more organisations that are classified as financial institutions in order to provide additional insights into the research problem. Furthermore, it is recommended for future studies to increase the sample size to increase the generalisability of the results and make better inferences. Different organisations may have different perspectives of BDA. In this study, 69% of the respondents had work experience of 10 years and above, for future studies the effect of seniority in financial institutions on the results can be measured. A framework measuring the direct correlations between independent variables and BDA adoption was presented in this study. However, for future research organisation age can be used as a moderator to analyse the relationship between independent and dependent factors. Since a cross-sectional data collection method was used, future research should use a longitudinal study that tests the relationships over a longer period of time. Future studies should look into the impact of the South African regulatory framework on implementing BDA in financial services organisations and their effectiveness in addressing data protection and privacy concerns.

5.7 Conclusion

Financial institutions rely on data for their operations, and many have migrated their data and applications to the cloud environment given that BD depends on the distributed database and cloud storage capabilities of cloud computing. Traditional systems are no longer capable of processing these large volumes and formats of data and many industries are adopting cloud-based BDA tools. Data is considered a valuable asset within organisations and being able to derive insights from the data is even more valuable. Organisations are reliant on analytical tools to make decisions that are more trustworthy, meaning that BDA has improved business productivity and effectiveness (Maroufkhani et al., 2020a). Financial institutions and other organisations derive several uses and benefits from BDA such as fraud detection, customer segmentation, personalisation, customer acquisition and retention, and customer reviews and sentiment analysis. Big data analytics offers a number of advantages to financial service providers as well as users, for instance financial institutions providing enhanced customer service and customers through a more customised and effective experience (Jamaludin et al., 2022).

The aim of this study was to develop a framework for the adoption of BDA in South African financial institutions. Relevant literature was reviewed to conceptualise the BDA framework and included the identification of relevant factors based on the conceptual framework design. The study examined BDA adoption in South African financial institutions, using the TOE framework as a theoretical basis. Of the proposed hypotheses six were accepted and three were not accepted. The study found that technological factors, technological characteristics, users perception towards technology, organisational factors due to top management support, individual characteristics and BD characteristics play a significant role in BDA adoption and led to the design of the final BDA adoption framework. Technologies for BD management offer data security and protection together with quick identification of illegal activity, indicating the importance of technological factors in BDA adoption (Jamaludin et al., 2022). The findings of this study highlight the importance of top management support in relation to BDA adoption (Lutfi et al., 2022a), as top leadership play a huge role in providing the resources needed for technology adoption, because organisations with limited resources and expertise might not be able to adopt BDA.

The study found that organisational factors, organisational factors due to size and structure of the organisation and environmental factors do not influence adoption of BDA. Much as environmental factors are not significant in adoption of BDA, it is still important for organisations to adhere to local data protection regulations and privacy laws when handling consumer related information. According to Sharma et al. (2023), regulators and customers alike require trust, since without it the reputation of the organisation might be negatively impacted. The findings of this study are meant to assist financial institutions become aware of the impact of the identified factors in BDA adoption. The suggested framework can assist in raising awareness of the factors that support or impede BDA adoption and organisations can determine their appropriateness.

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APPENDIX A: ETHICS CLEARANCE CERTIFICATE

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/DB2289224/598

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

This certificate is only valid if accompanied by formal permission from the relevant stakeholder(s).

Project title	The adoption of big data analytics in South African financial institutions
Investigator / Researcher	Mr Mzwandile Dlamini
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	2023/10/13
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@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

17 October 2023
Date:

APPENDIX B: LETTER REQUESTING PERMISSION

UNIVERSITY OF THE
WITWATERSRAND,
JOHANNESBURG

University of the Witwatersrand,
School of Commerce, Law and Management
011 717 8007

Re: Permission to conduct research at <removed for confidentiality>

My name is Mzwandile Dlamini, I am studying for a Master of Management in Digital Business in the School of Commerce, Law and Management at the University of the Witwatersrand. I am seeking permission to do research at <removed for confidentiality>.

I am conducting research on big data analytics adoption. The study title is "**A framework for the adoption of big data analytics in South African financial institutions**". The purpose of the study is to determine the factors influencing the adoption of big data analytics (BDA) and its benefits.

The research will entail collecting data from staff at head office. I request permission to get access to a staff mailing list. I will invite individuals from the following departments: information technology, marketing, risk management, compliance, credit, and loyalty/rewards to participate in this study. If they agree, they will be asked to complete an online survey questionnaire (close-ended) which should take about 15 minutes to complete. Anonymity and confidentiality are guaranteed by not needing to enter either the name of the respondent or organisation on the questionnaire. In addition, no confidential information about the organisation will be requested. The results will be communicated in a dissertation.

The research participants will not be advantaged or disadvantaged in any way. They will be reassured that they can withdraw their permission at any time during this project without any penalty. There are no foreseeable risks in participating in this study. The participants will not be paid for this study.

All research data will be destroyed after the study is completed and published.

I therefore request permission in writing to conduct my research at your organization. The permission letter should be on your organization's headed paper, signed and dated, and specifically referring to myself by name and the title of my study.

Please let me know if you require any further information. I look forward to your response as soon as is convenient.

Kind regards,

Mzwandile Dlamini

079 133 9785
2289224@students.wits.ac.za

Supervisor
Professor Billy Kalema
071 838 2896
bkalema@gmail.com

APPENDIX C: SAMPLE PARTICPATION LETTER

UNIVERSITY OF THE
WITWATERSRAND,
JOHANNESBURG

Good day

My name is Mzwandile Dlamini, I am a student in the Master of Management in Digital Business programme at the University of the Witwatersrand, Johannesburg. My supervisor is Professor Billy Kalema. I am conducting a research study about big data analytics adoption. The study title is "**A framework for the adoption of big data analytics in South African financial institutions**".

As an employee in a financial institution, you are invited to take part in this survey. The purpose of the study is to determine the factors influencing the adoption of big data analytics (BDA) in South African financial institutions and its benefits.

Your response is important and there are no right or wrong answers. This survey is both confidential and anonymous. Anonymity and confidentiality are guaranteed by not needing to enter your name on the questionnaire. Your participation is completely voluntary and involves no risk, penalty, or loss of benefits whether or not you participate. You may withdraw from the survey at any stage.

The first part of the survey captures some demographic data. Please tick whichever boxes are applicable. The second part of the survey comprises of statements, please indicate the extent to which you agree with each statement by ticking in the appropriate box. The entire survey should take between 10 to 15 minutes to complete. Please note that completing the survey and pressing SUBMIT can be taken to mean consent to the survey.

Thank you for considering participating. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za. Should have any questions during or wish to obtain the results of the survey, please contact me.

My contact details: 2289224@students.wits.ac.za, 079 133 9785
Supervisor's details: Professor Billy Kalema, 071 838 2896

Kind regards,
Mzwandile Dlamini
Student: Masters in Digital Business
School of Commerce, Law and Management
Wits Business School, Johannesburg

APPENDIX D: ORGANISATION APPROVAL LETTER

The organisation approval letter has been obtained and shared with the ethics committee. It has been requested that the organisational approval letter remain anonymous.

APPENDIX E: ONLINE QUESTIONNAIRE

This questionnaire consists of three sections.

Section A: Participants general information

Section B: Factors influencing big data analytics adoption

Section C: Participants' perceptions about big data analytics adoption

SECTION A: **GENERAL INFORMATION**

PLEASE MAKE A CROSS (X) IN THE APPROPRIATE BOX CORRESPONDING TO THE CHOICE OF YOUR ANSWER TO THE QUESTION.

1. **What is your gender?**

Female		Male	

2. **What is your age group?**

18-27 years		28-37 years		38-47 years		48-57 years		58 and above years	

3. **What is your highest level of Education?**

Grade 12 and Below		Diploma		Degree/ Advanced Diploma		Honours/ Post Graduate Diploma		Masters or PHD		Other, please specify	

4. **What is your overall working experience?**

0-5 years		6-10 years		11-15 years		16 -20 years		21-25 years		26 years and above	

5. **What business unit/department in your organisation are you working in?**

Information Technology	
Marketing	
Risk Management	
Compliance	
Credit	
Rewards	

6. **Are you aware of Big Data Analytics (BDA)?**

Yes		No	

SECTION B: CONSTRUCTS TO MEASURE BIG DATA ANALYTICS ADOPTION IN SOUTH AFRICAN FINANCIAL INSTITUTIONS

By using the rating scale from 1-5 where; 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree. Indicate your level of agreement or disagreement of the following statements:

7.0 TECHNOLOGICAL FACTORS *(the internal and external properties of technology that are influential in the adoption of big data analytics (BDA))*		**1**	**2**	**3**	**4**	**5**
7.1 TECHNOLOGY CHARACTERISTICS						
7.1.1	Our data analysis applications are compatible enough to incorporate BDA tools.					

7.1.2	The current data processing system can be upgraded to allow the incorporation of BDA tools.					
7.1.3	I am confident that our current data processing system is secure enough to handle big volumes of data.					
7.1.4	IT infrastructure in our organisation is available to support BDA related applications.					
7.2 USERS PERCEPTION OF TECHNOLOGY						
7.2.1	I am confident that adopting BDA will improve the quality of our decision making.					
7.2.2	I believe that learning to use the big data analytics tools will be easy for our employees.					
7.2.3	Our current data processing system can reliably be used to analyse big volumes of data.					
8.0 ORGANISATIONAL FACTORS (*this construct refers to the organisational setting, size and structure in relation to big data analytics adoption*)						
8.1 TOP MANAGEMENT SUPPORT						
8.1.1	The top management in our organisation support IT related budgets and such will ease the acquiring of BDA tools.					
8.1.2	Our organisation provide training for new IT innovations such as training to use BDA tools.					

8.1.3	Our IT staff has the expertise to support big data analytics adoption.					
8.1.4	Our human resources are always willing to employ staff with expertise of new IT innovations.					
8.2 SIZE AND STRUCTURE						
8.2.1	Our organisation has a culture of supporting the adoption of new IT innovations like BDA.					
8.2.2	Our management always communicates new developments and innovations before they are adopted.					
8.2.3	We have established policies and standards we follow before adopting new IT innovations.					
9.0 ENVIRONMENTAL FACTORS *(this construct refers to the environmental factors that can impact big data analytics adoption)*						
9.1	The pressure we get from our stakeholders to improve our service delivery enforces us to adopt BDA.					
9.2	Our vendors provide after sales service including training on new IT innovations like BDA.					
9.3	We follow national and international standards as well as data protection regulations and privacy laws when analysing our stakeholder data.					

10.0 INDIVIDUAL CHARACTERISTICS (*this construct refers to how humans behave individually***)**							
10.1	Our employees have positive attitude towards the adoption of new IT innovations like BDA.						
10.2	We have enough skills to adapt to the use of BDA tools.						
10.3	Our employees have a positive belief that using technology will improve the quality of their work.						
10.4	I believe it will be easier for our employees to learn using BDA tools.						
11.0 BIG DATA CHARACTERISTICS *(this construct refers to the characteristics of big data)*							
11.1	We receive large volumes of data on a daily basis from our stakeholders.						
11.2	Sometimes we need to do real-time analysis of the data we receive within our organisation.						
11.3	Data generated within our organisation comes from multiple sources.						
11.4	There are always uncertainties when huge amounts of data are received at high speed.						
11.5	I believe that analysing the big volume of data we receive within our organisation will add value to our decision making as well as to our return on investments.						

SECTION C: PERCEPTION OF BIG DATA ANALYTICS ADOPTION

12. In your opinion, experience and perception how do you see the success of adopting big data analytics within your organisation.

ITEM	**Low**	**Medium**	**High**	**Very High**	**Extremely High**
From the technology perspective					
From the organisation perspective					
From the environmental perspective					
From the individual perspective					