The factors influencing the adoption of Machine Learning for regulation by central banks in SADC

by

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A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in fulfillment of the requirements for the degree of master's in business administration

Johannesburg, 2024

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DEDICATION

The paper is dedicated to my family wife, son, grandmother and mother, whose unwavering love, support, and encouragement have been my guiding light throughout this journey. Your belief in me has fuelled my perseverance and determination to reach this milestone. I am forever grateful for your endless sacrifices and boundless encouragement. This achievement is as much yours as it is mine.

DECLARATION

I, Sibusiso Kunene, declare that this research report is my own work apart from as indicated in the references and acknowledgments. This report is submitted as per the requirements in partial fulfillment for the degree of master's in business administration through the University of the Witwatersrand, Business School Johannesburg.

Sibusiso Kunene

Centurion

Signed at ………………………………………………

29 **February**

On the …………………………….... Day of ………………………… 2024

ABSTRACT

The study investigates SADC central banks' readiness to adopt machine learning technologies with raw data collected through an online survey. Subsequently, the raw data was transformed into modellable data using principal component analysis and further fitted into the proposed logistic regression model design. The data underwent reliability and validity tests, which confirmed that the measurements of the constructs were consistent, reliable, and appropriately represented the intended constructions. Correlation analysis was employed to examine the hypotheses of the model, and multiple and stepwise regression were performed as additional tests of the model.

The results show that IT infrastructure is instrumental in enabling SADC central banks to implement machine learning capabilities. Top management is crucial for implementing ML, but adequate IT infrastructure is also essential. The regulatory environment and IT infrastructure indirectly influence SADC central banks' readiness to adopt ML capabilities, despite top management's direct impact. The derivable policy implication from these results is that working groups among the sampled SADC central banks need to be formed to address the noted shortcomings within IT infrastructure and regulatory-related aspects of this adoption holistically.

KEYWORDS

Machine Learning, TOE Framework, Central banks, Artificial Intelligence.

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LIST OF ACRONYMS

AI	Artificial Intelligence
RBS	Risk based supervision
TOE	Technological Organisational and Environment
SADC	Southern African Development Community
4IR	fourth industrial revolution
ML	Machine learning

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CHAPTER 1. INTRODUCTION

1.1 Background of the study

Machine Learning (ML) deals with developing computers that enhance their performance automatically by learning from experience (Jordan, M. I., & Mitchell, T. M. 2015). It is a fast-emerging technical discipline that combines computer science with statistics, playing a central role in Artificial Intelligence (AI) and data science. Advancements in ML have been propelled by the creation of new learning algorithms and theories, as well as the increasing abundance of data and affordable processing. Data-intensive machine-learning approaches are increasingly being utilized in various fields such as science, technology, and commerce, resulting in more data-driven decision-making in areas including education, regulatory, manufacturing, and healthcare industries, amongst others.

A number of African economies have lately seen technological transformations in all sectors of their economies. African economies want to leverage the potential of digital technology to promote economic inclusion, with a particular focus on enhancing the banking sector (Enaifoghe, 2021; Madichie and Hinson, 2022). Van Rensburg et al. (2021) reported that some African countries had witnessed technical progress. To significantly change most African societies, stakeholders must harness and scale up these advancements in technology.

As a result of the 2008/09 global financial crisis, central banks were assigned additional duties in terms of supervision and market oversight (Chakraborty and Joseph, 2017). Market developments have been influenced by financial and economic events of the past two decades, leading policymakers to recognize the importance of maintaining an effective corporate governance system (El Mokdad, 2022). Furthermore, El Mokdad (2022) highlights that the occurrence of hundreds of bank failures worldwide during and after the global financial crisis of 2007–2008 has brought significant attention to bank governance.

Baxter (2016) investigated the growing complexity faced by regulators in overseeing contemporary financial institutions and recommended that the regulators should create their own advanced automated supervision methods, clearly defining a role for RegTech solutions within their environment. RegTech tools give regulators "more accurate and real-time information," which makes compliance "easier for regulated entities" (Micheler & Whaley, 2020). The Institute of International Finance (IIF, 2016) defines regulatory technology (RegTech) as the use of new technologies to solve regulatory and compliance requirements more effectively and efficiently.

Research in African contexts about this field of study is still limited. The majority of the current literature focuses on contexts in countries and regions such as Europe, the USA, Asia, and Australia; hence, there is a significant lack of studies conducted in African contexts (Jean-Claude Maswana, 2024). The assessment of academic literature on the impact of adopting ML by central banks has discovered limited research in this specific domain; thus, this study contributes to the limited literature related to the adoption of ML by the central banks in SADC. The majority of the literature focuses on ML techniques and their applications, with a slight emphasis on central banks' adoption of ML.

1.2 Problem Statement

Central banks currently have access to an unprecedented amount of data, including information gathered from the internet and other sources, to assist in making monetary policy decisions (Kinywamaghana, A., & Steffen, S., 2021). The data mostly consists of credit card transactions, micro-transactions in e-commerce, public statistics, and financial market data. In 2020, 40% of central banks will incorporate big data into their policy-making processes, which is an increase from 30% in 2015 (Doerr et al., 2021). However, the utilization of big data by central banks is far less widespread than in the commercial sector (Tissot, 2018).

Organisations are presently leveraging ML techniques to derive value by providing meaning to their data, discovering underlying patterns, and unearthing crucial insights that were previously unattainable (Filipe, 2020). However, global banking regulators are currently facing challenges in efficiently and effectively supervising the banking sector due to significant technological advancements and digital transformation occurring within the industry (IFC, 2020). The Irving Fisher Committee (IFC) noted that this has resulted in a change in banking regulators' approach to technology adoption.

They now need to adjust to new data points and market disruptions in order to efficiently oversee and regulate the banking sector.

Traditional supervisory and regulatory approaches frequently rely on manual processes and rule-based systems, which can be time-consuming, resource-intensive, and restricted in their capacity to detect complex patterns and emerging dangers (Broeders and Prenio, 2018). ML has the ability to overcome these restrictions by employing powerful algorithms and big data analytics to find patterns, anomalies, and trends that may suggest possible risks or compliance issues (Javaid, M., Haleem, A., Singh, R. P., Suman, R., & Rab, S., (2022), ECB (2019).

Purdy and Daugherty (2016) state that advancements in ML, deep learning, natural language processing, robotics, speech recognition, and expert systems have had the most influence on the field of AI and its applications in business. However, data indicates that many organisations are hesitant to adopt machine learning due to the uncertainties surrounding the current business landscape (Wuest T, Weimer D, Irgens C, Thoben KD 2016).

Extant literature emphasise the need for skilled data professionals to be able to utilize advanced data analytics capabilities. (Chakraborty and Joseph, 2017) highlight that large dataset management and the effective development of learning systems necessitate both technical know-how and domain experience. This is because a combination of diverse skill sets is anticipated to offer superior guidance to decision-makers compared to a uniform approach.

Decision makers often hesitate to adopt ML due to uncertainty about the relationship between technological, organisational, and environmental factors and their intent. The problem statement centers around the need to understand and identify the success factors for ML adoption by central banks in the SADC region. This study will be guided by the following primary question: Which variables impact the implementation of ML technologies in central banks within the SADC region.?

The below secondary research questions will guide our study:

1. What are the relative effects of technological, organisational and environmental factors on central banks in the SADC region to adopt ML?

2. Which factors should central banks in the SADC region consider improving their readiness to adopt ML technologies.

The purpose of this research was to advance the body of knowledge on ML by offering a comprehensive analysis of its adoption and determining whether technological advancements can revolutionize supervisory and regulatory functions within the SADC region, thereby improving bank regulation.

This study presents and evaluates a framework for the adoption of ML (ML) using the Technology-Organisation-Environment (TOE) frameworks and analyses them in the specific context of the Southern African Development Community (SADC) region. The TOE framework comprises technological, environmental, and organisational aspects.

1.3 AIM AND OBJECTIVES OF THE STUDY

This study intends to identify success factors associated with the adoption of ML technologies by central banks in the SADC region.

The study aims to accomplish the following objectives in accordance with its purpose:

- Understand the variables that impact the implementation of ML technologies in central banks within the SADC region.
- Understand the relative effects of technological, organisational and environmental factors on the adoption of ML in central banks within the SADC region.

1.4 JUSTIFICATION OF THE STUDY

The technological revolution has just begun to affect all economic sectors in many African economies. African economies want to leverage the potential of digital technology to propel economic inclusion, with a particular focus on the financial sector (Enaifoghe, 2021; Madichie and Hinson, 2022). A few African countries have made certain technological achievements, according to van Rensburg et al. (2021). If technological improvements are to have a substantial impact on most African communities, they must be fully utilized and scaled up.

According to Cielinska et al. (2017), big data presents numerous opportunities for analysing detailed information about the financial institutions, requiring advanced data analytics capabilities. To enable more informed decision-making, banking regulators will need to effectively manage large datasets, which will increase the demand for reliable data mining techniques and financial statistical modelling, according to (Petropoulos, 2019). As a result of large volumes of data disclosed by supervised entities there is an emergent need for regulators to minimise increasing costs of supervision and regulation in order to improve the efficiency of their supervised functions, (Arner, D. W., Buckley, R. P., Zetzsche, D. A., & Veidt, R., 2020).

The adoption of ML tools by central banks in the SADC region has the potential to completely transform the way financial institutions are regulated. However, a crucial concern still exists regarding how prepared banks authorities are to adopt and use these cutting-edge technologies (Danielsson, Macrae, and Uthemann, 2020). While AI is still a developing technology, business leaders who want to implement it face the risk of being early adopters. Therefore, it is essential to provide a framework that helps business leaders make well-informed decisions about adopting AI (Rao, 2017). The approach presented in this study will aid business leaders in making judgments on the deployment of ML.

There is a limitation of quantitative empirical research that examine the adoption of ML at the firm level in respect to central banks. This study employs the TOE framework as a theoretical lens to assess the use of ML by central banks in the SADC region. This paper aims to fill a gap in the information systems (IS) literature by applying the TOE framework to analyse the adoption ML. The TOE framework has not been extensively used in understanding ML adoption specifically, which makes this research relevant.

Mariemuthu, C. (2019), The TOE framework has been applied in multiple contexts, however the impact of different technological, organisational, and environmental elements on adoption differs based on the specific technology and context of use. The TOE framework emphasizes that technological, organisational, and environmental factors play a significant role in explaining the adoption.

Recent studies on AI readiness and adoption suggest that there is limited research focusing on the firm-level (Hradecky et al., 2022; Jöhnk et al., 2021). This research will enhance the existing body of literature on impact studies regarding the implementation of ML as an emerging technology within an organisation.

Furthermore, this study will provide organisations with insights into the critical factors that need to be taken into account while adopting ML.

1.5 Delimitations of the Study

Outlining the parameters and extent of the research is the aim of delimitations. The study's scope was one of its limiting factors (Haegeman et al., 2013; Rubin & Babbie, 2016). The study is limited at firm level and focuses on the factors that influence the adoption of ML at the firm level, rather than on individuals employed by central banks. Furthermore, our scope will be limited to TOE Framework theory and the adoption of ML. There is no sufficient data and studies conducted in the area of central banking in SADC. A literature search by the authors did not reveal any studies that focus on SADC region central banks readiness to adopt the ML technologies.

1.6 Definition of terms

Central bank	the governing body that is responsible for formulating and implementing policies that have an impact on a nation's money supply Bordo (Michael D. 2007)
Big data	high-volume, high-velocity, and/or high-variety information assets necessitate creative, cost-effective information processing models that provide improved insight, decision-making, and process automation (Gartner, 2021).
Artificial Intelligence	is a subfield of computer science concerned with the creation of computer programs capable of carrying out duties that would normally require human intelligence (Chen, 2019).

Emerging technology	technologies that are still in the early phases of development but have the potential to have a big impact on society and the economy are known as emerging technologies (Mckinsey & Company, 2021).
Machine learning	is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without being explicitly programmed, (Jordan & Mitchell, 2015).
Bank supervision	Bank supervision is the process of monitoring and regulating banks to ensure that they operate safely and soundly, in compliance with applicable laws and regulations, and maintain financial stability (BCBS, 2019).
Emerging Technologies	Radical, fast-growing, new technologies or the development of existing technologies (Stăncioiu, 2017).

Table 1 Definitions

1.7 Assumptions

The data was gathered from questionnaires via survey format from central banks in the SADC region, focusing on their knowledge and industry readiness, and assumed factual responses, irrespective of regulatory authority functions.

1.8 Chapter Outline

1.8.1 Introduction

Chapter one highlights the background, research problem, research objective, rationale, limitations, significance, definitions, assumptions, and chapter outline.

1.8.2 Literature Review

Chapter two provides definitions of key terms including, History of ML, characteristic of ML, characteristics of central bank, and technology adoption theoretical foundations. The literature search focused on articles related to the readiness and adoption of AI proxied by ML - identified research using Google Scholar, WITS Digital Library, IEEE Xplore Digital Library, ProQuest and others research methods online. Also considered research published in peer-reviewed journals such as the International Journal of Information Management, Journal of Information Technology, and Communications of the ACM.

1.8.3 Research Methodology

Chapter three outlines the population, sampling, design paradigm, data collecting, data analysis techniques, quality assurance and potential study limit.

1.8.4 Presentation of Results

Chapter four provides an overview of the data screening process that takes into account outliers, missing data, and reverse scoring. Response profiling and an overview of the adoption of ML technologies will be provided. Data is decoded and analysed from which deductions are drawn.

1.8.5 Interpretation of Results

Chapter five provides an extensive analytical review of the data analysis findings, including a detailed examination of the findings related to hypothesis testing, that are presented in Chapter 4. and any other revelations gleaned from the data.

1.8.6 Conclusion and recommendations

Chapter six concludes the research report, by examining the findings of the ML-adoption study, provides recommendations for central banks, and suggests potential areas for future research. The chapter will elaborate on the outcomes for academia and practice.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

The study will focus the current body of knowledge regarding AI technologies, specifically the ML concept, ML adoption and the TOE framework which will be explored to assess the importance of ML adoption and proposes its applicability in the adoption of ML by central banks in SADC region. Prior research on the adoption of technology utilising the TOE framework and its related elements is highlighted.

The chapter begins by providing various definitions of ML including central banks' duties and proceeds to describe the approach taken to the systematic literature review as well as exploring existing literature on the organisational adoption of IT using the TOE framework. The literature will further assess whether advanced data analytics such as ML techniques can help central bank regulators to revamp their existing processes.

2.2 Conceptual understanding of the key terms

2.2.1 History of ML

AI is a collection of software and programs designed to integrate with various applications, rather than a single technology. The AI applications are categorized based on how their cognitive capabilities measure up to human intelligence (Zhu et al., 2020). AI utilization has significantly risen in various industries, particularly in financial services. ML (ML) is a subset of AI (AI) that involves machines enhancing their performance autonomously without explicit human instructions (Brynjolfsson & McAfee, 2017).

The discipline of AI was formed in 1950s, whereby List Processing Language (LISP), created by John McCarthy in 1957, is considered one of the most influential and old programming languages (Mijwel, M. M. (2015). LISP is a programming language that enables the creation of dynamic programs that manipulate fundamental processes using list structures. From 1980 onwards, AI started being utilized in significant projects with practical purposes and has subsequently been modified to address real-world issues (Mijwel, M. M. (2015).

Over the years, many definitions of ML have been suggested, with Samuel (1959) and Mitchell (1997) being particularly well-known for their contributions to the field. However, Murphy (2012) provides a clear definition of ML as a collection of techniques that may identify patterns in data and utilize these patterns to forecast future data or make decisions in uncertain situations.

ML is defined is a statistical approach to studying and making inferences about data that utilizes a variety of algorithms suited for answering different types of questions (Algren, Fisher & Landis, 2021). There are three main types of ML: supervised, unsupervised, and reinforcement learning.

- supervised learning. Learning techniques that extract associations between independent attributes and a designated dependent attribute (the label)
- unsupervised learning. Learning techniques that group instances without a prespecified dependent attribute.
- reinforcement learning is a learning technique that directs the action to maximize the reward of an immediate action and those following.

According to L'heureux et. al (2017), all algorithm and ML modification options (with or without new paradigms) put a strong emphasis on enabling the processing of huge datasets, enhancing performance, or enabling real-time processing. Kolisetty & Rajput (2020), big data analytics solutions deliver excellent performance in a short amount of time by supplying innovative scientific advancements that may be linked with ML systems for decision-making.

The widespread availability and affordability of big data platforms, coupled with advancements in computational resources, have made it easier and more efficient to train large ML models using extensive historical data (Chiang, Enke, Wu, & Wang, 2016; Chilimbi, Suzue, Apacible, Kalyanaraman, & kitchin, 2014). Moreover, the proliferation of increasingly advanced ML algorithms has played a significant role in the surge in its popularity, hence ML has become the preferred method in AI (AI) for creating useful software in areas such as computer vision, audio recognition, natural language processing, robot control, and other applications.

Kinywamaghana and Steffen (2021) stated that ML not only brings new tools but addresses unique challenges compared to traditional economic approaches and techniques. ML techniques primarily concentrate on predicting outcomes rather than estimating parameters, which was a common feature of conventional approaches and applications (Mullanaithan and Spiess, 2017). Organisations that effectively use and develop AI technology will enhance their competitiveness and foster AI-driven capabilities (Logg et al., 2019).

However, research indicates that a significant portion of organisations still have little confidence in ML adoption, primarily due to the unpredictability of today's business environment (Wuest, T. et al. 2016); managerial reluctance to justify investment and manage risks (Canhoto, A. I. et al. 2020); a lack of ML expertise (Bauer, M. et al. 2020); and complex IT infrastructure (Lavin, A. et al. 2022). Furthermore, there is little empirical research has been done on the factors influencing the adoption at the firm level, (Filipe, P et al. 2023).

2.2.2 Applications of ML in Central Banks

Central banking regulators are in upheaval as the speed of technological development is transforming the banking ecosystem, resulting in rapid digital transformation, and changing the banking business model which increases risk exposure and ultimately impacts financial stability. With the adoption of advanced data analytics and implementation of ML within the regulatory environment, the situation may be improved if central bank regulators could efficiently analyse the huge volumes of data that are generated and gathered to produce better and more detailed insights (arias, 2017).

Following the 2008/9 global financial crisis, central banks' responsibilities have since expanded. The fourth industrial revolution includes the digitalization of the global economy, focusing on ML, big data, and AI (AI) to enhance all aspects of economic activity (Poloz, 2021). AI (AI) and ML (ML) have been increasingly important in central banking decisions in recent years (Kinywamaghana, A., & Steffen, S. (2021).

A study conducted by Jaure in 2023 demonstrated that ML techniques can be successfully used to address challenges associated with large datasets in Central Banking. This approach offers practical answers to data management problems and enhances the precision and effectiveness of crucial economic indicators Jaure, M. R. (2023).

Ahmed (2023) states that big data is used in conjunction with ML applications in various areas, including monetary policy, financial stability, and research. Furthermore, the author highlights that Central banks utilize big data for supervision and regulation. The Bank for International Settlements (BIS) states that ML (ML) can enhance the precision of bank failure prediction models, decrease incorrect identifications, and accelerate the process of developing and implementing models (BIS, 2021).

In recent decades, there has been a rise in the scrutiny and understanding of central bank communication (Blinder et al., 2008). Natural Language Processing (NLP) a subset of ML technique, has become prominent in central banking research with numerous high-quality studies, Zahner, (20212). Researchers have several approaches to quantifying qualitative information. Gentzkow, Kelly, et al. (2019) offer a comprehensive survey on utilizing text data, particularly in the field of economics. Schmeling and Wagner (2019) showed that central bank communication affects asset prices. Ehrmann and Wabitsch (2021) analysed Twitter data to investigate central banks' communication with non-experts. Ehrmann and Talmi (2020) examined the impact of semantic similarity in central bank statements on market volatility.

In this study by Larry Catá (2018), data-driven decision-making in the regulatory domain is examined from a governance viewpoint. The paper demonstrates how data-driven governance systems are reshaping state and other government entities' regulatory environments. These governance systems, which are founded on accountability principles and integrated with incentive-based systems for lowering risk and controlling behaviors through mechanisms of choice and markets, have the potential to change the structure and operation of states and other governance organs. Advancements in ML have enabled the development of intelligent systems with cognitive abilities, like Siri and Alexa, which help businesses enhance decision-making and customer service Janiesch et al., 2021.

Central banks have utilized ML techniques to enhance their regulatory and supervisory tasks. Below are examples of its utilization by central banks:

Banking supervision

Prudential supervision plays an important role in ensuring that institutions are financially healthy and capable of meeting their obligations to investors (Misoi, 2014). The European Central Bank (ECB) and South Africa Reserve Bank (SARB) have carried out several Supervisory Technology (SupTech) initiatives, such as the enhancement of their data analytics capability by automating reports (ECB, 2021; SARB, 2020). The PRA utilized regulatory information from credit unions to create early-warning criteria for supervisory purposes in monitoring credit unions (Coen, J et al (2017).

Central bank communication

There is a place for AI/ML going -forward, especially in data collecting and data analyses, even if decisions will ultimately depend on the supervisors' judgment. Currently, many authorities from Financial Stability Board member countries use ML and Natural language processing (NLP) techniques for data analysis, processing, validation, and plausibility (FSB,2020). Zahner and Baumgärtner (2022) developed a language model utilizing ML approaches to identify words and texts in a multidimensional vector space to analyse and interpret central bank communication. The language model successfully extracted pertinent data from public speeches to predict future monetary policy shocks.

Anti-money laundering and financial crime

The ECB found that ML can increase the detection of money laundering and terrorism financing, as well as enhance the efficiency of transaction monitoring (ECB, 2020). Furthermore, AI can enhance the efficacy and efficiency of financial crime investigations and risk management in both financial and non-financial entities (Proudman, 2018). Project Aurora by the BIS Innovation Hub used money laundering data to evaluate the effectiveness of different traditional and ML algorithms in identifying fraudulent payments (BISIH (2023)). The models, such as neural networks and isolation forests, are trained using synthetic money laundering transactions to forecast the probability of money laundering in new data de (Araujo, D. K. G et al (2024).

Processing of complaints

The Bank of Italy has implemented a new software solution utilizing AI techniques to enhance the processing of information in complaints. It assists the bank by identifying major trends promptly and conducting thorough investigations and comparative studies to aid in regulatory, supervisory, and financial education activities, (Bank of Italy 2021).

Credit risk analysis and scoring

The adoption of innovative technologies and methodologies to enhance risk assessment activities in the financial technology sector is a growing trend (Milian et al., 2019). ML techniques, along with deep learning (DL) to a certain degree, have been applied to evaluate credit risk and anticipate bank failures in recent years (Guerra, P., & Castelli, M. (2021).

2.2.3 Information Technology Adoption

Oliveira, T., & Martins, M. F. (2011), It is widely acknowledged nowadays that IT has a substantial impact on organisations' productivity. These effects will only be completely recognized when IT is broadly disseminated and utilized. It is essential to understand the factors influencing IT adoption and the theoretical models developed to explain IT adoption. Technology adoption in advanced countries may vary from that in developing countries due to differing challenges in different contexts (Molla and Licker, 2005).

When considering various concepts of technology adoption, the quality, availability, and expense of infrastructure access have impeded the progress of many developing nations (Humphrey et al., 2003). The study focused on small and medium-sized enterprises, and discovered that developing nations frequently lack the technological resources, qualified personnel, and businesses that are essential for adopting electronic commerce (Humphrey et al., 2003).

Kim & Eunil (2020) identified user resistance, privacy issues, trust, accessibility, perception of prices , and perception of technology usage and benefits as potential difficulties in the adoption process. Jeon et al. (2020) acknowledge that technical complexity, prediction accuracy, and the repercussions of consumer technology usage perception, as well as financial concerns, are potential barriers to successful technological innovation adoption.

Information Systems (IS) research utilizes numerous hypotheses (Wade 2009). This paper will only focus on hypotheses related to the adoption of technology. Fishbein and Ajzen's (1975) theory of reasoned action (TRA) was one of the initial models to be formulated. The Theory of Planned Behavior (TPB) by Ajzen (1985, 1991). Ajzen (1991) enhances the TRA by incorporating perceived behavioral control as a third factor, into the theory of planned behavior (TPB). On the contrary, user intentions regarding technology adoption were absent from both TRA and TPB (Cruz et al., 2010).

The Technology Acceptance Model (TAM) by Davis (1986, 1989), In addition to perceived usefulness and perceived simplicity of use, TAM takes into account additional factors not considered in TPB (Cruz et al., 2010). The Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh and others (2003). Chen, (2019), expands upon Technology Acceptance Model 2 to forecast users' behavioral intentions regarding the adoption and utilization of technology. The above-mentioned adoption models are at the individual level.

At a firm- level, the Diffusion of Innovations (DOI) by Rogers (1995), hypothesis and explains that the process, reasons, and speed at which new ideas and technologies disseminate throughout cultures, function at the individual and company level. The Technology-Organisation-Environment (TOE) framework by Tornatzky and Fleischer (1990), offers a practical analytical structure that can be applied to the examination of the adoption and assimilation processes of various forms of IT innovation. While the above models are among the most commonly used theories, this study primarily focuses on utilising the TOE framework to assess the factors that impact the adoption of ML by Central banks in the SADC region.

2.2.4 Technology-Organisation-Environment (TOE) Framework

Tornatzky and Fleischer (1990) developed the TOE framework to improve IT effectiveness in organisations. TOE was developed to address organisations' requirements for adopting and implementing innovations in technology. Organisational conditions have a substantial impact on Central banks' decisions to use ML/AI and utilize the advantages of advanced analytics.

The TOE framework has shown a robust theoretical basis, reliable empirical support, and possible relevance in various information systems fields (Baker, 2012). This theory has been described as a rationalistic goal-oriented theory by Al Nahian et al. (2009). Therefore, TOE can be used to examine the adoption of any technology, due to its generic character (Zhu et al., 2003; Liao et al., 1999). Chan, F. T. et al. (2013), further highlights that the TOE framework provides a strong theoretical foundation and reliable empirical measures for analysing adoption across many fields of information systems. (Bijker and Hart 2013, argue that the elements within this framework can be seen as both limiting and driving forces for specific technological innovation adoption inside the organisation.

The TOE framework is a theory at the firm level that explains three specific factors of organisations' adoption decisions (Oliveira and Martins, 2011). Tornatzky and Fleischer explain that the TOE framework offers an advantageous analytical framework that can be applied to research how various types of IT innovation are adopted and assimilated.

The three factors are the technological context, organisational context, and environmental context, each considered to have an impact on technological innovation:

(a) Technological context refers to both the internal and external technologies relevant to the organisation.
(b) Organisational context refers to descriptive parameters in relation to the organisation, such as managerial structure, and size.
(c) Environmental context in which a company operates, including its market, its rivals, and its interactions with the government, Tornatzky and Fleischer, 1990).

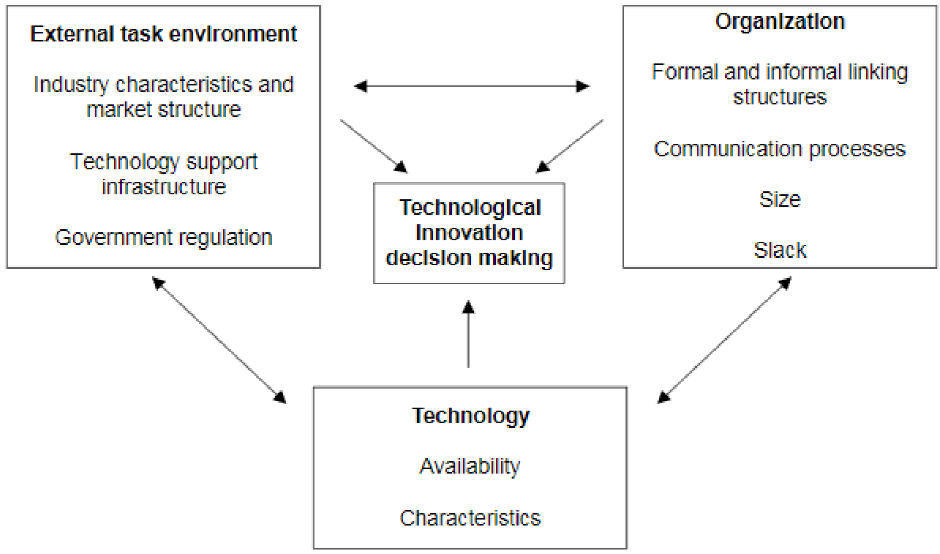

Figure 1: Technology, organisation, and environment framework (Tornatzky & Fleischer, 1990)

The TOE framework is recognized as the model that provides a holistic assessment of the factors determining the adoption of technology (Chittipaka, V et al. (2023). TOE has been identified as an effective approach for identifying value creation and innovation acceptability (Gangwar et al. 2015) and Senyo et al. 2016). Furthermore, it is also believed that the TOE framework could offer higher insights by analysing both the external and internal dynamics of organisations (Tornatzky et al., 1990).

The TOE has been extensively used in the existing innovations including the Internet of things ((Hsu & Yeh, 2017).), cloud computing ((Hiran & Henten, 2020; Khayer et al., 2020), and blockchain (Chan, F. T. S., & Chong, A. Y.-L. (2013), and there is an opportunity to broaden TOE's domain of research to ML adoption (Filipe, P., Ruivo, P., and Oliveira, T. (2023). The TOE framework is recognized as a strong and appropriate model for examining the factors that influence technology adoption by businesses (Awa & Ojiabo,2016).

Technological factors, namely technology competence, which comprises technological structure and IT expertise, were considered significant (K. Zhu, Kraemer, et al., 2006; K. Zhu, Dong, Xu, & Kraemer, 2006; Venkatesh & Bala, 2012; K. Zhu & Kraemer, 2005). Top management support has been highlighted in the organisational context as crucial for aligning the organisation's interests with new technologies and it is widely acknowledged in academic literature as a crucial factor influencing the success of IT projects (2011 Pumplun et al., 2019; Maduku, Mpinganjira, & Duh, 2016).

Top management support was identified as crucial in the organisational context (Chan & Chong, 2013; Oliveira et al., 2014, Malik et al., 2021). Regulatory support was identified as the most significant factor in the environmental context (Bose & Luo, 2011; Oliveira et al., 2014; Thomas, Costa, & Oliveira, 2016; K. Zhu & Kraemer, 2005).

Oliveira, T., Martins, R., Sarker, S., Thomas, M., & Popovič, A. (2019) examined the direct and moderator effects of the TOE framework in the SaaS setting through empirical analysis. The study specifically investigated the factors influencing the adoption of Software as a Service (SaaS) by applying the technological, organisational, and environmental perspectives of the TOE framework. They analysed the factors influencing Software as a Service (SaaS) adoption within organisations by combining the TOE framework with the INT theory.

The TOE framework was redesigned to analyse both its direct impacts and its moderator effects. The study found that technological, organisational, and environmental contexts play a substantial role in influencing SaaS adoption. The environmental context directly influences SaaS adoption and also affects the relationship between technological context and SaaS adoption. Filipe, P., Ruivo, P., and Oliveira, T. (2023) investigated the impacts of the TOE framework.

In terms of evaluating the use of ML in companies with an emphasis on how the environmental context influences this process. The results indicated that external influences could influence adoption with less emphasis on the technology factor. Additionally, the environmental context plays a moderating role in the relationship between technology and adoption. Further research is required to comprehensively examine the factors that influence the adoption of ML in organisations, across various industries and different countries.

Historically, academics have prioritized the technical progress and enhancement of AI technology over its adoption, which has been relatively overlooked (Alsheibani et al., 2018). Therefore, there is a chance to broaden the use of the TOE framework in the adoption of ML by Central banks.

2.3 THEORETICAL FRAMEWORK

2.3.1 Research Empirical Methodology

This section outlines the conceptual model for examining the TOE framework's effectiveness in assessing SADC central banks' readiness to adopt ML capabilities based on stakeholders' insights on technological, organisational, and environmental contexts. Consequently, the justification for applying the theoretical lens of the Technology and Innovation (TOE) framework to analyse the technological innovation under investigation is that, according to the literature currently in publication, this framework allows one to understand the larger context in which the tested innovation takes place by incorporating the various technical, organisational, and environmental influences into their respective contexts (Baker, 2012; Bose & Luo, 2011; Venkatesh & Bala, 2012). (see below figure 2).

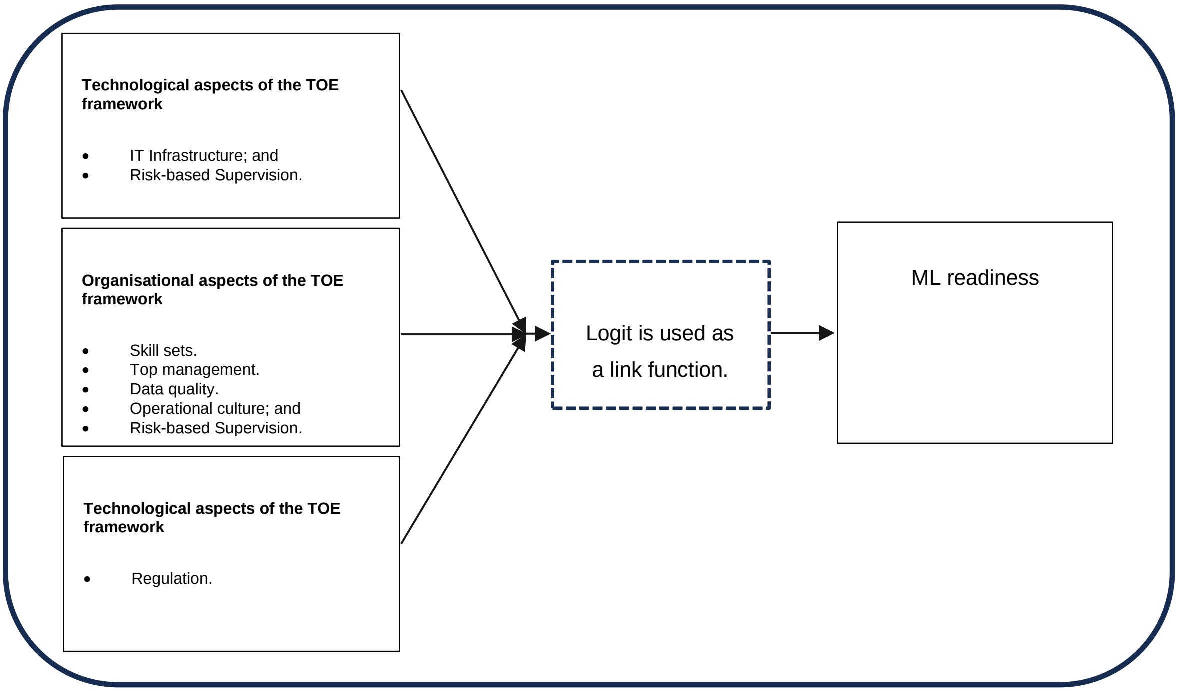

Figure 2: Conceptual framework of the model design

ML Adoption is the dependent variable in the conceptual model in Fig. 2 is the ML adoption. It is a discrete binary variable that is assigned a “1” if the company has already implemented an ML. Otherwise, ML adoption holds a “0.”

Technological context

In the existing literature, technological resources have been consistently identified as an important factor for successful information systems adoption. Limited information technology infrastructures hinder the continued development of online commerce (Chircu and Kauffman, 2000).

Technology competency includes the technical infrastructure and human expertise that can impact a company's adoption of an innovation (K. Zhu & Kraemer, 2005). Intense competition within the industry sector boosts the adoption of technology (Mansfield et al., 1977). Tornatzky and Fleischer (1990) stated that the increasing variety of new technology options available can create challenges for businesses in identifying their needs and selecting the most suitable technological solution.

The firm is more likely to reject the new technology adoption plan if it is deemed incompatible with current technology or business operations, Yoon et al. (2014). According to Baker (2012), while adopting new technologies, organisations should think about the kinds of modifications to the operations that will happen because some technologies will have a more significant influence than others which will have a smaller one.

Małgorzata and Szyma (2008) define Risk-Based Supervision (RBS) as a methodical approach that focuses on identifying the most significant risks confronting an organisation. It involves a detailed evaluation by a supervisor to assess how these risks are managed and the organisation's susceptibility to potential adverse events. Supervisors must create and apply strong risk assessment procedures and standards to prevent the risk of failing to effectively and promptly assess risks (Barth, 2002). Momanyi, C. J. (2009), states that the IT infrastructure allowed the Chilean Banking authorities to gather and analyse submitted bank returns promptly. Furthermore, the author stated that through risk-based supervision, supervisory teams were able to focus on high-risk areas with the assistance of strong IT software. Data quality is a crucial component in guaranteeing the efficacy of risk-based supervision, according to a Basel Committee on Banking Supervision (2013) study on risk data reporting and aggregation. For ML to be effective, data quality is essential (Breck, Polyzotis, Roy, Whang & Zinkevich, 2018). High-quality data is required to ensure that the resulting innovation meets its objectives, (Eljasik-Swoboda, Rathgeber, & Hasenauer, 2019).

Organisational context

Igwe et al. (2020) highlighted those organisational capabilities such as inadequate technical, human, time, and management resources, as well as a lack of top-management support, might pose barriers to the successful implementation of technological innovation adoption projects in a company. Baker (2012) states that while many studies emphasize the importance of an organisation's surplus resources in facilitating innovation adoption, other research suggests that innovation adoption can occur even without these resources.

Wang and Wang (2016) discovered that there was a significant amount of top-management endorsement in companies that implemented knowledge management systems. Effective organisational and technological infrastructure is crucial for the success of information technology systems used by firms (Khayer et al., 2020). The use of developing technologies such as natural language processing, text mining, video/voice/image analytics, and visual analytics must be handled by experts, according to Schultz (2013). Data quality in an organisation is associated with factors like accessibility, precision, timeliness, integrity, dependability, and security, Wang, R. Y., & Strong, D. M. (1996). In order to embrace innovation, a company needs IT capabilities, which include data, IT infrastructure, IT standards and strategies, and other intangible assets (Mariemuthu, 2019).

Organisational culture significantly affects a company's ability to reap the full benefits of digital technologies, according to Kane et al. (2015). Venkatraman (1994), as referenced by (Parida et al., 2016), provided a paradigm in which the proper use of IT deployment is subject to existing corporate culture principles. Organisational readiness has been discussed across a variety of fields, including business management, healthcare, information systems, and organisation science (Armenakis, Harris, and Mossholder, 1993; Oliver & Demiris, 2004; Snyder-Halpern, 2001). However, several people have given different definitions of this idea and no single definition has been agreed upon (Weiner, Amick, & Lee, 2008; Lokuge et al., 2019; Dyerson et al., 2016).

Environment context

Tornatzky and Fleischer (1990) defined structures in environmental factors, which include industrial characteristics, government regulations, and technology supporting infrastructure. Sociological research on models indicates that individuals' decisions to participate in a specific behavior are influenced by the perceived number of people in the surroundings who have previously done so, (Krassa, M. A. (1988). If a sufficient number of comparable organisations behave in a specific manner, causing a particular course of action to become widespread in the industry, other organisations will imitate to prevent the risk of being seen as less innovative or less adaptable (Goodstein, J. D. (1994).

The technology adoption process may be impacted by the organisation's external regulatory environment, Sjöberg, R., & Schill, D. (2023). According to Baker (2012), government regulation can either foster or stifle innovation. For instance, newly enforced privacy laws may limit an organisation's ability to offer novel means for customers to access their data. The findings of research conducted (Dwivedi et al., 2021) suggested that the General Data Protection Regulation (GDPR) is a problem when implementing AI.

A regulatory environment is one in which organisations must abide by rules, policies, and regulations set forth by the government. According to Hart and Saunders [1997], the acceptance of innovations is significantly influenced by the regulatory environment. The introduction of disruptive technology to any industry is complicated and plagued with difficulties such as regulations (Sivarajah, Irani, & Weerakkody, 2015; Sivarajah, Kamal, Irani, & Weerakkody, 2017).

Lu et al. (2014) note that security is a significant problem and contend that the phenomena of big data will not be widely accepted if security challenges are not adequately managed. Several recent studies identified government regulatory support as the primary environmental element driving technology adoption within the TOE framework (Naser et al., 2022; Spinelli, 2016). The research will mainly focus on the government regulatory aspect within the TOE framework.

From a theoretical perspective Tornatzky and Fleischer (1990), explain that an enterprise's decision to adopt an innovation is influenced by technological, organisational, and environmental factors, including technology availability, organisational structure, industry structure, technological support infrastructure, and government regulations.

Technology competency includes the technical infrastructure and human expertise that can impact a company's adoption of an innovation (K. Zhu & Kraemer, 2005). Furthermore, based on the existing literature (Orji, I. J., Kusi-Sarpong, S., Huang, S., & Vazquez-Brust, D. (2020). Oliveira, T., Martins, R., Sarker, S., Thomas, M., & Popovič, A. (2019). Awa, H. O., & Ojiabo, O. U. (2016).), expected outcomes estimated unknown coefficients of factors proxying the technological and organisational context, such as top management, should be positive and statistically significant. However, because it is assumed that the regulation acting as a proxy for this context is a deterrent (undeveloped to support such development) Albrecht, S., Reichert, S., Schmid, J., Strüker, J., Neumann, D., & Fridgen, G. (2018)., therefore, the estimated unobserved factor for the environmental context is expected to be negative and statistically significant.

2.4 Conclusion of Literature Review

Organisations adopt emerging technologies for value creation such as digital-enabled opportunities as well as rationalisation of certain aspects of the organisation, amongst others to ensure sustainability and survival over time. The success of the adoption of these technologies is based on the understanding of what the value ultimately looks like and the required strategy to achieve that. Many organisations undertake the process of digital transformation without understanding what this ultimately looks like, what the impact would be, and ultimately what the risks associated with this; Cybersecurity is a critical risk based on the impact introduced by the adoption of these technologies, making organisations more susceptible to this type of risk. This is further heightened by the implementation of specific emerging technologies that create immediate change within the environment (Grahn et al., 2021). Major people, process, or system changes in the organisation, requires a major increase in cybersecurity investment as well, however, according to Li et al. (2021), increased cybersecurity investments do not necessarily result in lower security breaches in organisations. Furthermore, they note that organisations that are less digitally advanced with fewer cybersecurity controls are not necessarily less susceptible to those organisations that are highly digitalised with greater investments in cybersecurity (Li et al., 2021). The result highlighted that the increased investment could lead to higher security breaches in these digitally transformed businesses due to easier access to data via digital platforms (Rogowski, 2013).

Relevant mitigating controls are either internal or external facing controls; and breaches whether internal or external are reduced by investing in certain controls such as network controls from an external perspective whereas internal breaches are reduced by implementing other controls such as user identity and access security controls (Li et al., 2021). It is often advised that a controlled environment is only as strong as its weakest point and therefore, organisations may have the best and most expensive cybersecurity controls to complement their digital transformation, however, if there is a small vulnerability that exists, the organisation will be exposed to cyber threats (WEF, 2022). Organisations need to ensure that their transformation strategies are combined with suitable cybersecurity strategies to ensure an overall effective cybersecurity posture.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the data collection process including the various data transformations performed on the collected data set to enable the information to be modelled statistically. Lastly, this chapter presents the model design utilised to provide insights into the research objectives defined in Chapter One. The remainder of the chapter is arranged as follows: Section 3.2 outlines the data collection methods used and the performed transformations on the collected data (note that this section also outlines the variables that are omitted from the analysis due to technical difficulties observed from surveyed literature studies). Section 3.3 presents the research model design, while Section 3.4 outlines the ethical considerations, and Section 3.5 highlights observed limitations within the elected research design in this study. This chapter is concluded by Section 3.6 which outlines salient takeaways from the discussed research methodology presented.

3.2 Data, data collection process, and data transformations

Section 3.2 outlines the data collected, its processes, and the rationale for using a particular research paradigm including critical data transformations that were applied to the raw information to enable statistical modelling of the collected data. The study examines the impact of the TOE framework on SADC central banks' readiness to incorporate ML into their supervisory and regulatory functions (that is, the assumption is that these institutions have begun exploring some of the technical concepts and technologies required for such a technological implementation). Furthermore, the nature of data required to resolve the overarching objective of this study is through an online questionnaire sent to key stakeholders in the SADC central bank sector responsible for successful implementation and change management concerning technological innovation embedment to the traditional ways of work of central banks in this region.

The following are some of the questions that were asked to the sampled stakeholders of SADC central banks concerning the successful embedment of ML into their functionalities.

- The adoption of ML has the potential to identify risks that may be missed by traditional methods.
- Your department has a well-established IT infrastructure to support the implementation of ML.
- Top management actively promotes and supports the adoption of ML across different departments and functions.
- Government laws and regulations are stable and clear to support ML initiatives and implementation.
- What is the stage of ML/AI adoption in your organisation.

We employed the "key information" approach for data gathering as described by Oliveira et al. (2014) and Pinsonneault & Kraemer (1993). This method proved beneficial in selecting eligible participants. According to Alchemer (2018), exploratory data analysis helps researchers find missing or incorrect data, create a map of the data's underlying structure, determine which variables have the most impact, and identify and highlight outliers and anomalies. We created a questionnaire and used Qualtrics to design our online survey. The answers to our questions were recorded using a 5-point Likert scale. A total number of 100 potential respondents were identified and contacted to participate in the survey; however, we received 60 responses, with a response rate of 96%. Furthermore, 60 responses were screened to identify missing data .15 responses were removed due to data quality issues such as duplicates and incomplete responses, and subsequently deleted from the dataset. Therefore, the number of eligible respondents was adjusted to 45.

In addition to the normal questions, we have also created specific questions tailored to the context of machine learning. This study utilised SPSS version 28 for statistical analysis.

The 5 Linkert scale response mechanic were used to qualify the responses that the interviewer could select except in the case of the final question since a three-categorical scale was used as the possible response that the stakeholder in the sample could select. The discrete nature of the collected information meant that various data transformations were a necessity to transpose the raw information collected from the surveying processes into a dataset that is modellable statistically. However, before this transformation, the Cronbach alpha statistic was computed per category of data groupings to establish the reliability of the collected information. The first computation signaled that some of the questions based on this statistic, and the attained outcomes reported the same insights. This was common under the questions asked concerning IT infrastructure and data quality. In the case of such scenarios, the questions that were correlated were removed from the analysis before computing the transformed variables incorporated into the model.

Kutner et al. (2005) demonstrated that a discrete variable can be transformed into modellable variables by creating unique groups (denoted by n) minus one (n-1) dummy variable. The resulting dummy variables were above 80 variables and when fitted into the model design defined in Section 3.3 below, results reported numerous errors due the large dimension of the data versus the number of observations received post the data collection process. To correct this the principal component analysis was utilised as defined by Hair Jr. et al. (2010) which by design reduces the dimension of the revised data (dummy variables) into singular variables per set of group of dummy variables through using the eigenvalue mathematics to determine the respective index (that is the sum product of factor loadings with an eigenvalue greater or equals to one and the respective dummy variables considered in this analysis). In addition, the computed principal component variables; and their means were subtracted from each observation and divided by their standard deviation statistics to standardise the created variables used in the model. Although in the data collection process (survey questionnaire), questions around data quality, risk-based supervision, skills set, and organisational culture were omitted from this analysis due to the following reasons.

In conclusion, the statistics outlined below were also computed given that only valid 45 observations were successfully collected from the data collection process outlined above.

- Total response rate = total number of responses / total number in the sample – ineligible.

- Active response rate = total number of responses / total number in the sample – (ineligible + unreachable).

The above-mentioned statistics were computed to ensure that the responses received align with responses received from other similar studies surveyed in this research. This survey was sent to the stakeholders on 03 December 2023 and responses were received end of January 2024.

3.3 Validity and Reliability

The data obtained from the online survey was analysed to identify any errors, missing data, or instances where respondents supplied ratings outside the specified range (Creswell, 2012). After gathering the data, it was analysed using SPSS, a statistical software application. Validity testing was conducted on the measuring scales. Construct validity refers to the extent to which a measurement scale accurately measures the theoretical concept it is designed to measure (Bhattacherjee, 2012).

The reliability of the measurement scales was also assessed. Internal consistency reliability assesses the degree of consistency among many items that evaluate the same constructs (Bhattacherjee, 2012). When participants are given a measure that includes numerous items, the degree to which they rank those things similarly reflects internal consistency. Creswell (2012) states that Cronbach's alpha is a useful tool for estimating the reliability of internal consistency. A coefficient of 0.93 is considered high, while a coefficient of 0.72 is considered good.

3.4 Model design

This section aims to outline the model design to empirically test the research objective outlined in Section 2.3, whether it is identifiable as to which context of the TOE framework, should SADC central banks focus on if they were to be compliant with adopting ML capability.

In Section 3.2, it was determined that to explore this analysis effectively the deductive research paradigm with a statistically explanatory mechanism would be used.

This section outlines the conceptual model for examining the TOE framework's effectiveness in assessing SADC central banks' readiness to adopt ML capabilities based on stakeholders' insights on technological, organisational, and environmental contexts.

Furthermore, the TOE framework from an extant literature basis (Baker, 2012, Bose & Luo, 2011; Venkatesh & Bala, 2012) found that the TOE framework is an effective explanatory method of discovering whether the subject under review is ready to implement the technological innovation in question.

In this current, the assumption is that the time spent in developing the required skill to understand ML and its application in regulation will translate into those SADC central bank being ready to implement ML capabilities into its regulatory supervision functions.

Empirically, the preceding statement is defined as follows:

From a theoretical perspective Tornatzky and Fleischer (1990), explain that an enterprise's decision to adopt an innovation is influenced by technological, organisational, and environmental factors, including technology availability, organisational structure, industry structure, technological support infrastructure, and government regulations. Technology competency includes the technical infrastructure and human expertise that can impact a company's adoption of an innovation (K. Zhu & Kraemer, 2005). Furthermore, based on the existing literature (Orji, I. J., Kusi-Sarpong, S., Huang, S., & Vazquez-Brust, D. (2020). Oliveira, T., Martins, R., Sarker, S., Thomas, M., & Popovič, A. (2019). Awa, H. O., & Ojiabo, O. U. (2016).), expected outcomes estimated unknown coefficients of factors proxying the technological and organisational context, such as top management, should be positive and statistically significant. However, because it is assumed that the regulation acting as a proxy for this context is a deterrent (undeveloped to support such development) Albrecht, S., Reichert, S., Schmid, J., Strüker, J., Neumann, D., & Fridgen, G. (2018)., therefore, the estimated unobserved factor for the environmental context is expected to be negative and statistically significant. The baseline regression model is defined as follows (the objective of the baseline regression outlined below is to examine whether the attention played by SADC central banks is sufficient to enable the ML capabilities from the regulatory perspective):

$$MLAI\_Adoption_i = \alpha(MLA_i) + \varepsilon i \qquad \text{Eq (1)}$$

Where: $MLAI\_Adoption_i$ denotes SADC central banks' readiness to implement ML capabilities while the MLA_i depicts these central banks readiness by evaluating from the current processes whether they are ready to adopt ML in its functionalities. "i" denotes the responses from SADC central banks and ε_i is the error term.

The $MLAI\_Adoption_i$ is a dummy variable that takes 1 if SADC central banks are exploring ML capabilities and 0 otherwise. While the MLA_i variable is also a dummy variable, it takes 1 if SADC central banks' responses indicate their readiness to implement ML capabilities and 0 otherwise. The logistic regression model design is used for this analysis (due to how the response variable is defined). Therefore, equation (1) is re-written (where $MLAI\_Adoption_i$ is denoted as ln(p/(1-p))) as follows:

$$\ln(p/(1-p)) = \alpha(MLA_i)+ \varepsilon_i \qquad \text{Eq (2)}$$

In addition, if the attention placed by SADC central banks is sufficient and on par, the expectation is that the estimated α should be positive and statistically significant. In subsequent equations, the intention is to assess whether the significance level and sign of the unknown coefficient changes if the TOE factors are considered in the estimation of equation (2) defined above. The first model considers the inclusion of a factor proxying the technological context while the second model adds the top management which proxy the organisational context of the TOE framework and the third model includes the regulation factor which proxy the environmental context of this framework.

$$\ln(p/(1-p)) = \alpha(MLA_i) + \beta(Infr_i) + \varepsilon_i \qquad \text{Eq (3)}$$

Where: $Infr_i$ denotes the variable that outlines an index of infrastructure development towards the adoption of ML (proxy the technological context) and β is the corresponding unknown coefficient.

$$\ln(p/(1-p)) = \alpha(MLA_i)+ \beta(Infr_i)+\upsilon(TM_i)+\varepsilon_i \qquad \text{Eq (4)}$$

Where: TM_i denotes the variable that outlines an index of top management views toward the adoption of ML (proxy the organisational context) and υ is the corresponding unknown coefficient.

$$\ln(p/(1-p)) = \alpha(MLA_i) + \beta(Infr_i) + \upsilon(TM_i) + \gamma(Reg_i) + \varepsilon_i \qquad \text{Eq (5)}$$

Where: Reg_i denotes the variable that outlines an index of regulation readiness with respect to the adoption of ML (proxy the organisational context) and γ is the corresponding unknown coefficient.

For all fitted logistic regression model designs defined above to test their goodness of fit is achieved by evaluating the Nagelkerke R-square measure and the F statistic.

3.5 Ethical considerations

According to Creswell & Creswell (2018), ethical issues are crucial considerations in every study. According to Thomas and Hodges (2013), research ethics refers to the set of standards that researchers must follow when engaging with participants. Carpenter (2019) asserts that the primary emphasis in ethical evaluations of quantitative research, such as experiments, lies on the documented technique and results. The University of Witwatersrand's research adheres to strict ethical conditions, including informed consent, anonymity, and confidentiality of participants. The School of Economics and Business Sciences approved the study with protocol number WBS/BA2506503/326.

3.5.1 Informed consent

Cahana and Hurst (2008) argue that informed consent is crucial in research as it empowers participants to make autonomous decisions about their involvement in the study. Cahana and Hurst (2008) state that the components of informed consent are typically explained through the concepts of disclosure, understanding, decision-making ability, and willingness to participate. This research employed a voluntary participation survey, allowing respondents to independently decide whether or not to engage in the study.

3.5.2 Rights to Privacy

The anonymity and confidentiality of the respondent's identity and personal information will be protected to ensure their privacy during the analysis, interpretation, and reporting of the data.

3.6 Limitations

The study has limitations, particularly in its sample size. Firstly, the study had a low response rate, and increasing the sample size could potentially change the relationships observed between underlying explanatory variables and ML adoption variables computed. Secondly, the logistic regression model used to predict ML adoption by central banks has its limitations, including potential shortcomings in accurately capturing the complexities of adoption dynamics, especially in the dynamic and evolving technology landscape.

3.7 Summary

In Chapter 3 the focus was on outlining the data collection, and data transformation including the removal of certain variables collected due to their adverse effects on the reliability of the collected information. Secondly, the model design used to investigate the overarching research objective outlined in Section 3.2 was defined including its operational perimeters. In conclusion, this chapter continues by outlining the possible limitations of the research design. The following chapter will discuss in depth the results from the descriptive analysis, and data validity test including the evidence from the applied model design.

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

This chapter outlines the descriptive analysis process to summarise and interpret the characteristics and features of the data to facilitate understanding and interpretation. Secondly, this chapter presents the model results to obtain insights into our data and the hypotheses. Thirdly, this chapter will provide the findings obtained from statistical or mathematical models contextualised in relation to the research objectives defined in Chapter One. The remainder of the chapter is arranged as follows: Section 4.2 outlines the descriptive analysis. Section 4.3 presents the model results to analyse and explain the implications of the results and highlight key findings in the data. This chapter concludes with Section 4.4 which outlines a critical discussion of the model results offering insights into the research questions, theoretical implications, and practical implications of the study.

This section aims to outline the empirical analysis of the proposed model design in Section 3.3, which examines the impact of ML capabilities on SADC central banks' ability to successfully implement this technological strategy using the theoretical TOE framework.

4.2 Descriptive statistical analysis

In this section, we present a descriptive statistical analysis of the correlation matrix for all variables examined in the study. The correlation matrix, depicted in Table 1, provides valuable insights into the relationships among the explanatory variables, elucidating patterns of association and potential dependencies which are crucial for understanding the underlying dynamics of the data.

Table 1 : Correlation matrix of all explanatory variables

Variable Name	Data Quality	Skill set	Organisational Culture	Risk-based supervision	IT Infrastructure	Top Management	Regulation
Data Quality	1.000						
Skill set	0.680[a]	1.000					
Organisational culture	0.847[a]	0.632[a]	1.000				
Risk-based supervision	0.638[a]	0.446[a]	0.588[a]	1.000			
IT infrastructure	0.701[a]	0.565[a]	0.642[a]	0.485[a]	1.000		
Top Management	0.850[a]	0.576[a]	0.809[a]	0.584[a]	0.774[a]	1.000	
Regulation	0.503[a]	0.512[a]	0.469[a]	0.490[a]	0.509[a]	0.492[a]	1.000

Notes: a, b, and c reflect the applied significance level which is denoted by 1%, 5%, and 10% respectively. The table above represents the correlation matrix computed using the Spearman's rho non-parametric method.

The data quality variable is positive and statistically correlated to organisational culture, infrastructure, and top management at a 1% significance level and these correlation statistics are 0.847, 0.701, and 0.850 respectively. These results imply that data quality with the previously mentioned variables correlate to the highest degree and are probable candidates to increase multicollinearity in the proposed model design outlined in Section 3.3.

Further, it was noted that another problematic pair might be the correlation between top management and infrastructure including top management and organisational culture as these correlation metrics are 0.774 and 0.809 respectively at a 1% significance level.

The questions answered in the survey for the organisational context were top management, organisational culture, and skill set (with the skill set being the exception to the rule); given that there were issues with these variables being correlated, it was required to sort of determine the appropriate presentation for this cluster. Given that the assessed technological innovation's readiness is based on the TOE framework, extant literature by Tornatzky et al. (1990). opted to proxy this category using the top management variable. For this reason, the top management variable was included in the study as opposed to other variables noted here.

Lastly, another point to note from the reported results is that the IT infrastructure and risk-based supervision rather measure the technological aspect of the TOE framework. However, as per reported results, this pair significant correlation result is not an issue as it is lower than the 0.700 threshold used to depict high correlation among explanatory variables. However, given that for the organisational context discussed above, a single variable was used to proxy this category; the same methodology is followed in selecting the variable to include in the analysis, which is based on surveyed literature, which indicates that the IT infrastructure variable is chosen as supposed to the risk-based supervision.

Within this section, we will provide the findings of Spearman's rho correlation, which was conducted to investigate the connections between all explanatory variables used in the model. A summary of the findings as shown in Table 2, provide insights into the degree and direction of associations between the variables under investigation.

Table 2: Spearman Rho's correlation analysis for the explanatory variables used in the model.

Variable Name	IT Infrastructure	Top Management	Regulation
IT Infrastructure	1.000		
Top Management	0.774[a]	1.000	
Regulation	0.509[a]	0.492[a]	1.000

Notes: a, b, and c reflect the applied significance level which is denoted by 1%, 5%, and 10% respectively. The table above represents the correlation matrix computed using the Spearman's rho non-parametric method.

Table 2 denotes the Spearman rho's correlation for the variables that would be incorporated into the model to answer the research objectives highlighted in Section 1. Only the correlation pair between IT infrastructure and top management is found to be high (0.774 at 1% significance level) as per the threshold outline in the discussion of Figure 3. However, despite this noted high correlation, it was decided that all of these variables should be included in the analysis, and in addition goodness-of-fit tests will be used to monitor the probable implication of multicollinearity through the R-squared measure.

As illustrated in Table 3, categorical variables are profiled for ML adoption and ML readiness studied to provide a complete overview of their distribution, frequency, and attributes, to assess whether there are major patterns and trends within the two variables.

Table 3: Profiling of the categorical variables

Categorical levels	Variable name	
	Machine Learning (Adoption)	Machine Learning (Readiness)
0	32	35
1	13	10

Table 3 outlines the profile structure for the categorical variables included in the model design where ML (adoption) is the response variable. The assumption made in developing the model design is that SADC central banks that invest efforts and change in mindsets when coming to ML capabilities over a period of time would translate in these institutions being ready to implement such technological innovation when required by best practice (used to formulate the baseline model).

The correlation matrix table, depicted in Table 4, provides insights into the relationships among the explanatory variables, to determine patterns of association and potential dependencies which are crucial for understanding the underlying dynamics of variables used in the model,

Table 4 : Correlation matrix between the response variable and the explanatory variables

Variable name	IT Infrastructure	Top Management	Regulation	Machine Learning (Readiness)	Machine Learning (Adoption)
IT Infrastructure	1.000				
Top Management	0.774[b]	1.000			
Regulation	0.509[a]	0.492[a]	1.000		
Machine Learning (Readiness)	0.192	0.301	0.230	1.000	
Machine Learning (Adoption)	0.045	0.258	0.109	0.249	1.000

Notes: a, b, and c reflect the applied significance level which is denoted by 1%, 5%, and 10% respectively. The table above represents the correlation matrix computed using the Spearman's rho non-parametric method.

Table 4 outlines the correlation figures between the response variable—ML (Adoption)—and the respective explanatory variables which are IT infrastructure, top management, regulation, and ML (readiness). This result shows that the response variable is not statistically significant to any of the explanatory variables fitted in the regression analysis which suggests that the probability of endogeneity (i.e., the relationship between the response and the error term on the left-hand side of the equation). The significance of this result suggests that there is no need to collect additional data to identify the origins of the responses collected in this study (panel regression is not required).

The research framework's constructs were assessed using Cronbach's alpha, a confirmatory factor analysis metric to examine internal consistency for all the constructs and whether they acquired an acceptable value that is above 0.7000 (Hair et al., 2019)., as shown in Table 5.

Table 5: Cronbach alpha per considered cluster in the model data.

Variable cluster	Cronbach alpha statistics
IT infrastructure (Q1 to Q6)	0.833
Top Management (Q24 to Q27)	0.884
Regulation (Q33 to Q36)	0.716
Machine Learning (Readiness)—Q37 to Q41	0.762

Note: The threshold set at 0.7000 which indicates that the questions are gathering information that is unrelated to other questions within a particular cluster.

Table 5 reports the reliability analysis run for the various groups of questions asked in the survey stage. For the following variables—IT infrastructure and top management had a Cronbach alpha way greater than the expected 0.7000 threshold set with the extant literature (Hair et al., 2019). In hindsight, this result highlights that future studies in this discipline when collecting data or creating research instruments in a form of questions for the IT infrastructure and top management need to pay critical attention to the similarities that might arise when seeking insights on these developments with respect to the testing of technological innovation readiness as studied in this present research.

Similarly, the correlation tables noted above highlighted this shortcoming because the Spearman rho's correlation was positive and statistically significant at a 1% significance level with a correlation measure equal to 0.774 which is regarded as high in the context of this study. However, the rationale for not re-issuing the questions for the affected groups is that the overall implication of possible multicollinearity was muted by the data transformations applied to the raw data. Furthermore, in terms of regulation and ML (readiness) the computed Cronbach alpha indicates that future studies need to as well look into getting questions that yield dissimilar insight to reduce these statistics; however, at this point is not a major concern because it does not translate into highly correlated variables.

4.3 Model results

This section aims to outline the empirical analysis of the proposed model design in Section 3.3, which Figure 8 shows, the relationships between the predictor and outcome variables, while also assessing the goodness-of-fit statistics to ascertain the robustness and reliability of the regression model to examine the impact of ML capabilities on SADC central banks' ability to successfully implement this technological strategy using the theoretical TOE framework.

Table 6: Regression analysis.

Variable definition	Model 1 (Baseline)		Model 2 (Baseline + Technological context)		Model 3 (Baseline + semi-complete TOE framework)		Model 4 (Baseline + complete TOE framework)	
	Coefficient (significance level as power)	Exp(Coeff)	Coefficient (significance level as power)	Exp(Coeff)	Coefficient (significance level as power)	Exp(Coeff)	Coefficient (significance level as power)	Exp(Coeff)
MLA	-1.216[a]	0.296	-1.214[a]	0.297	-1.569[b]	0.208	-1.569[b]	0.208
STD_IT_Inf			0.020	1.020	-1.401[b]	0.246	-1.403[b]	0.246
STD_TM					2.473[b]	11.860	2.465[b]	11.769
STD_RG							0.016	1.017
Goodness-of-fit statistics								
Number of observations	45		45		45		45	
Nagelkerke R square	0.287		0.287		0.434		0.434	
Overall correctness on classification of the response variable	0.711		0.711		75.6		75.6	

Table 6: note a, b, and c denote the significance level used which are namely—1%, 5%, 10%

The response variable considered in the regression analysis outlined in Table 6, is a binary variable that assigns 1 to scenarios where central banks have begun building the capabilities of understanding ML and required technologies or otherwise is o for those that have just begun looking at this construct. Given the nature of response variable logistic regression model design will be implemented across all models reported in Table 6. Therefore, to assess all models' performance the following goodness-of-fit test statistics need to be computed which are the Nagelkerke R-squared measure and the odds of correctly assigning the different categories considered in the response variable.

Model 1 is a baseline logistic regression model suggesting that central banks' investment in understanding and building ML capabilities could enhance their readiness to adopt technological innovation from the above-mentioned technology. Models 2 to 4 reported in Table 6, denote logistic regressions where the central bank's investments in understanding and building ML capabilities are a function of these institutions' state of readiness to implement this technology, plus considering the effects specified within the TOE framework. For example, in model 2 the response variable equals ML readiness of SADC central banks plus IT infrastructure (proxy of T in the TOE framework applied in the study) while in model 3 the response variable is all explanatory variables in model 2 plus top management (proxy of O in the TOE framework).

This paper aims to establish whether the TOE framework is an applicable/feasible tool to assess SADC central banks' ML capabilities given the development in their technology, organisation, and environment. However, according to the first objective stated in Chapter 1, the proxies for the various factors under the TOE framework are expected to be positively and statistically significant at the designated alpha as outlined under the results. In the case of this study, the theoretical expectations were not met as the technology factor which is proxied by MLA is negative and statistically significant, while the organisation factor which is proxied by Infrastructure was positively and statistically insignificant.

The implications of these deviations noted above suggested that the TM variable of these SADC Central Banks needs to deliver a strategy to align its technological and organisational advances in such a way that such developments contribute positively to these institutions' ability to embed ML processes into their core functions. Interestingly it is the environmental factor that is proxied by TM that aligns with the theoretical expectation because its coefficient was found to be positive and statistically significant in the relative TOE framework analysis outlined in the methodology chapter. The following were the attained results: In the case of model 1, the coefficient (-1.216) of MLA is negative and statistically significant at a 1% significant level. Furthermore, in this model, we find that there associated predicted probability is -0.704 (0.296-1) indicating that there is a negative relationship between the independent variable and the predicted odds. Based on the reported outcome although MLA is statistically significant since the computed odd ratio is negative suggests that the likelihood of this scenario materialising is minimal. This further implies that we may need to consider proxies of the TOE framework to establish which of its factors are not correctly aligned to enable SADC central banks' readiness to implement ML capabilities despite some of these institutions already placing a value investment in such technologies. This result suggests that if SADC central banks invest time and efforts in understanding the technologies and frameworks around ML, should in theory translate into being able to adopt such technology when required by best practices for this sector (this is due to the negative odd outcome reported above).

In model 2, the coefficient (-1.214) of MLA remains negative and statistically significant at a 1% significance level with a negative odd (-0.703). In addition, the coefficient of IT infrastructure was found positively insignificant with positive predicted odds of 0.020 (1.020-1). The results imply that SADC central banks' expertise in ML will not translate into increasing their ability to implement such technology successfully due to the lack of technological developments in the SADC region (proxied by IT infrastructure).

Furthermore, in model 3 the coefficients of MLA and IT infrastructure remain a stumbling block for SADC central banks to implement ML based technological innovations as witnessed in the discussion of model 2 above. Interestingly in model 3 the consideration of top management in the modelling process has yielded a positive and statistically significant coefficient at a 5% significance level with exp(coefficient) equals 11. 860. These results imply that an increase of 1 point would increase the odds of top management by (11.860-1) *100 percent. This result reported above demonstrates that the organisational aspect of the TOE framework enables SADC central banks to implement ML capabilities technologies.

In model 4, the coefficients MLA, IT Inf, and TM bear similar interpretations discussed above and the focus in this results interpretation is on the coefficient of regulation which is positive and statistically insignificant with an odd of 1.7 percent. These model results are the same as the case discussed in model 2 for the infrastructure variable thus implying that the regulation environment within the SADC region is not yet comprehensive and mature enough to enable their Central banks' capability to implement ML as a technological innovation.

In the second objective, if the TOE framework in the case of SADC central banks' was working effectively in assessing the adoption of ML into its core functions, the expectation was that when introducing new factors into the baseline model defined in the methodology chapter is that previously included variables would remain positively significant with a marginal increase with the size of the coefficient given that you have more information to analyse.

However, in the case of this study given that our empirical results deviate from the theoretical assertion derived in the literature indicates that there are major gaps in terms of technology and organisational aspects within SADC Central Banks in implementing this technology. This further implies that the relative effectiveness analysis, the paper wanted to demonstrate was not met thus suggesting for related future studies more proxies of these factors need to be collected or the scope of study in terms of the covered countries needs to be expanded for empirical results and technological results to align if the shortcoming of effective analysis was originating from the sample analysed being too limited. Possibly, if the shortcoming of this effective analysis is not from the data, then the implications outlined in the first objective analysis need to be effected and allow SADC central banks to accumulate data before redoing this analysis.

4.4 Discussion of the model results

The objective of the current study is to investigate the readiness of SADC central banks to adopt machine learning capabilities into their functionality given that these institutions are machine learning proficient in implementation. The data collection process comprises gathering primary data through issuing an online survey on the subject and subsequently transforming raw data into modellable data using dummy variable creation theory (Kuner et al.,2005) and principal component analysis (Hair Jr. et al., 2010). The model design used is a logistic regression on premisses that the modelled response variable is binary in nature that is one of the Central Banks has begun building expertise on machine learning or zero otherwise.

This response variable is regressed against a binary variable testing SADC central banks' readiness to implement the suggested technology, including the factors proxying the effects of the TOE framework. The following are the findings reported: first, the model results indicate that while IT infrastructure doesn't directly impact ML adoption in SADC central banks, IT infrastructure is instrumental to these institutions' readiness to implement ML capabilities as a technological innovation strategy into their daily functions. Second, the model results further show that the top management in SADC central banks is crucial for implementing ML as a technological innovation strategy, but adequate IT infrastructure is also essential for the successful implementation of such technology in their functionalities. Finally, the model results demonstrate that the regulatory environment and IT infrastructure indirectly influence SADC central banks' readiness to adopt ML capabilities, despite top management's direct impact.

First, the model results indicate that while IT infrastructure doesn't directly impact ML adoption in SADC central banks, IT infrastructure is found to be instrumental to the readiness of these institutions to implement ML capabilities as a technological innovation strategy into their daily functions. Mariemuthu, C. (2019) partially agrees with the finding that IT infrastructure does not affect the adoption of technological innovation, but the lack of sophisticated IT infrastructure in SADC central banks hinders their readiness to implement such technological strategies. However, this finding contradicts prior studies by (Pumplun et al., 2019; Hamm & Klesel, 2021;), which indicate that technological infrastructure is the most crucial factor for companies in facilitating the adoption of technology.

Second, the model results further show that the top management in SADC central banks is crucial for implementing ML as a technological innovation strategy, but adequate IT infrastructure is also essential for the successful implementation of such technology in their functionalities. Similar results have been found in earlier research (Alsheibani et al., 2020; Chen et al., 2021; Pillai & Sivathanu, 2020), which found that both IT Infrastructure which is proxied as technical capabilities and top management are positively significant in impacting the readiness to implement technological innovation strategies and this finding agrees with the evidence reported above. This indicates that the central banks that participated in the research recognize the significance of endorsement from the top management with regard to the implementation of AI. However, (Alghamdi, 2020; Al-Alak & Alnawas, 2011; Bueno & Gallego, 2017, partially disagrees with the finding that top management enables the readiness of an institution to implement technological innovation successfully because in this scenario relative relevancy which proxies the IT infrastructure is found to be positively significant which is not the case in terms of the current results.

The rationale for the noted difference might probably be due to the fact that in the case of the SADC central bank, the need or the requirement for these institutions to evaluate ML capabilities as an innovation strategy has been going for some time which allowed their top management to be appraised with the development in this technology, however, in the case of extant literature top management influences on the applied technological innovation was limited given that the technology its self is still in its infancy and the process is being looked at rigorously to understand what is happening from a top management perspective. The conditions under which top management plays a critical role in adopting technological development is when time has been given or questioned for some time.

The model results further demonstrate that the regulatory environment and IT infrastructure indirectly influence SADC central banks' readiness to adopt ML capabilities, despite top management's direct impact. The results show that government regulations have a detrimental impact on the intention of adopting AI, so government regulation is not supported. While the finding aligned with Horani et al. (2023), This may indicate that there is a lack of regulations governing the use of AI-driven technologies. Government laws and regulations, especially those related to privacy, security, and data access, can significantly enhance the development of the AI ecosystem. However, this finding contradicts prior studies by Pan et al. (2022) and Dora et al. (2022) as well as Alghamdi (2020) which suggest that organisations must adhere to government laws and regulations to effectively utilize AI-driven technologies. Additionally, global economic and technical development is being propelled by advanced economies. The developed world will always be ahead of the curve when it comes to adopting new technology, like AI. With regard to emerging markets, the organisations' hesitation to embrace new technologies has slowed their ability to implement cutting-edge solutions.

Although the research fulfills the paper's objectives and goals, acknowledging certain limitations is crucial to ensure the reliability of the findings. To begin with, it is important to note that the research is limited in scope to the Central Bank fraternity in the SADC exclusively. Various internal and external factors can impact the adoption of AI and ML in each industry. While certain elements, such as IT infrastructure and managerial support, are universal across industries, the findings of this study may not be directly applicable to other sectors.

In addition, the framework only takes a limited number of elements into account because of the constraints of time and scope. To assess the impact of additional factors on Central Banks' adoption of AI and ML, future studies can take industry characteristics, relative advantage, and compatibility into account.

CHAPTER 5. Conclusion, recommendation, and future research

5.1 Introduction

This chapter outlines the descriptive analysis process to summarise and interpret the characteristics and features of the data to facilitate understanding and interpretation. Secondly, this chapter presents the model results to obtain insights into our data and the hypotheses. Thirdly, this chapter will provide the findings obtained from statistical or mathematical models contextualised in relation to the research objectives defined in Chapter One. The remainder of the chapter is arranged as follows: Section 4.2 outlines the descriptive analysis. Section 4.3 presents the model results to analyse and explain the implications of the results and highlight key findings in the data. This chapter concludes with Section 4.4 which outlines a critical discussion of the model results offering insights into the research questions, theoretical implications, and practical implications of the study.

5.2 Conclusion of the research study

In conclusion, SADC central banks' adoption of ML depends on the development of global best practices concerning ML related regulatory environments and significant IT infrastructure developments. Also, for SADC central banks top management is found to be a determinant required to enhance SADC central banks' readiness to adopt machine learning capability which is not sufficient due to the above-mentioned shortcomings. The SADC central banking sector is not ready to integrate machine learning into its functionality due to insufficient regulatory strategies and IT infrastructure.

5.3 Summary of Findings

The main results of this analysis show that IT infrastructure is crucial for SADC central banks to adopt ML as a technological innovation strategy. Furthermore, the model results also argue that top management as a proxy for organisational context is essential but not sufficient to enable the technological capabilities mentioned in the first finding. Finally, the model evidence shows that the regulatory environment and IT infrastructure indirectly influence ML adoption readiness.

5.4 Limitations

The study has limitations, including a low response rate which may adversely impact the overall goodness of fit test of the fitted model design (full content is described in Section 3.5). Furthermore, the number of responses in this study was limited to 45. The adoption of ML technologies could have been influenced differently if there were more responses, which would have affected the relative effects of the TOE components.

The TOE framework is inadequate in capturing all the elements that impact the adoption of ML. Therefore, enhancements can be implemented to the model by incorporating and evaluating other factors.

5.5 Recommendations

This study recommends that the SADC central banking sector efficiently integrate ML capabilities by aligning top management expectations with the necessary IT infrastructure developments and a conducive regulatory environment that supports such technological advances.

Given the observed favourable correlation between TM support and the adoption of ML, it is advisable for Central Banks to prioritise their attention on TM. By emphasising the advantages of ML for Central Banks, TM can provide motivation and have a favorable position to influence the adoption of ML by assuring support and the availability of resources for its implementation. It is crucial for top managers to comprehend the significant impact they have in influencing the acceptance and implementation of cutting-edge technologies within the organisation.

5.6 Suggestions for further research

The main focus of this study was the TOE framework. Additional research on the implementation of ML in Central Banks could be examined using an alternative theoretical framework. The TOE framework lacks a conclusive model illustrating the elements that impact a firm's decisions to adopt, therefore allowing for potential enhancements to the model. Further factors can be replaced to enhance the precision of forecasting the adoption of ML technologies, and the model of this study can be employed as a basis for further development.

In future studies when building research instruments, researchers need to pay special attention to the construction of the questions that provide insights into IT infrastructure and top management. The overall questions, they are some degree of similarity in the questions, however, regulation is the only variable within reasonable limit with a Cronbach alpha close to the threshold.

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APPENDIX A

Wits Business School
Sculpting global leaders

The factors influencing the adoption of ML for bank regulation by central banks in SADC region

IT Infrastructure (1: strongly disagree; 5: strongly agree)

1. Your department has a well-established IT infrastructure to support the implementation of ML.
2. Our IT infrastructure is flexible and scalable enough to handle the computational requirements of ML algorithms.
3. Your department has a robust data architecture and IT infrastructure that enables efficient storage, retrieval, and processing of large datasets for ML.
4. Our department regularly evaluates and adapts its IT infrastructure to support advancements in ML technologies.
5. The current technological infrastructure supports seamless integration for risk based supervision.
6. Our IT capabilities are suitable to protect the privacy and security of our networks and systems.

Data quality (1: strongly disagree; 5: strongly agree)

1. The quality of your department's data is sufficient for training and deploying ML models.
2. Our department has invested in data strategy including data governance practices to ensure the accuracy and reliability of our data.
3. Your department has well-defined processes for data collection, cleansing, and preparation for ML purposes.
4. Our department has mechanisms in place to ensure the security and privacy of data is prioritised before being used in ML algorithms.

5. Your department actively tracks and measures the impact of ML on our business performance and outcomes.

Risk Based supervision

1. The current technology infrastructure in your department adequately supports risk based supervision
2. Implementing ML algorithms would enhance data analysis capabilities within your supervisory process.
3. The outdated technology infrastructure hinder the effectiveness of traditional supervisory activities for risk based supervision
4. Our departments existing technological tools support real-time risk monitoring and analysis in our department’s supervisory process
5. Our department embraces that ML could mitigate the identified limitations of traditional supervisory activities for risk based supervision
6. Your traditional supervisory practices align with the demands if risk-based supervision

Skill set (1: strongly disagree; 5: strongly agree)

1. Our department has a skilled workforce with the necessary expertise to develop and maintain ML models.
2. Our department actively invests in training programs to enhance the skills of employees in ML.
3. Your department has a dedicated team responsible for monitoring and maintaining the performance of ML models.
4. Your department actively collaborates with external partners or vendors to access specialized ML expertise.
5. Inadequate resources and inappropriate personnel are a significant challenge for the adoption of ML.

Top management (1: strongly disagree; 5: strongly agree)

1. Top management is aware of the potential benefits and risks associated with adopting ML.

2. Top management has clear strategy for integrating ML into your existing business processes.
3. Top management actively promotes and supports the adoption of ML across different departments and functions.
4. There is a culture that encourages experimentation and learning from failures when adopting ML.
5. Our senior managers have strong understanding of how ML tools can be utilised to increase risk based supervision

Organisation culture/readiness (1: strongly disagree; 5: strongly agree)

1. Your organisation encourages and supports the adoption of new technology for learning and development purposes
2. Our organisation actively promotes a culture of innovation and experimentation including the use of ML
3. Our organisation provides sufficient training and development opportunities for employees to learn about ML
4. There is a culture of trust and openness that enables sharing and utilization of ML knowledge and insights
5. Decision-making processes within the organisation are influenced by data-driven insights

Regulatory environment (1: strongly disagree; 5: strongly agree)

1. Government laws and regulations are stable and clear to support ML initiatives and implementation.
2. Our department has clear strategy and roadmap for incorporating ML into your supervision process.
3. Your department regularly assesses the ethical and legal implications of using ML in your risk-based supervision.
4. An industry movement towards the adoption of ML tool could place pressure on your organisation

ML adoption

1. A timely ML technical implementation and application migration plan has been developed
2. The adoption of ML has been already endorsed by top management
3. The budget and timeline schedule have been approved
4. We become efficient and effective in our supervisory process
5. The adoption of ML has potential to identify risks that may be missed by traditional methods.

General (descriptive analysis)

1. Have ML/AI tools been adopted in your department, if so, indicate which area is the main focus.
    a. Risk assessment
    b. Policy analysis
    c. Fraud detection
    d. Data quality
    e. Don't know/unsure
    f. Other, please specify

2. **What is the stage of ML/AI adoption in your organisation? (select one)**
    a. Just looking
    b. Early adopter (we've had models in prof for 2+ yrs)
    c. Sophisticated (we've had models in prof for 5+ yrs)

3. Who determines the key metrics for project success? (select one)
    a. Data sciences leads
    b. Product managers
    c. Exec Staff
    d. Other

4. To what extent, if any, is the risk control department in your firm using big data analysis and ML techniques for estimating risk (either operational risk, market risk, or regulatory risk)?
    a. Investigating its use
    b. In the process of implementing these tools
    c. Using in limited applications
    d. Widespread use
    e. Don’t know/unsure

5. Company age: bank supervision
    a. 0 – 10 years
    b. 10 – 20 years
    c. 20 – 30 years
    d. 30 – 40 years
    e. Over 40 years

6. Position level
    a. Junior-level
    b. Mid-level
    c. Senior- level

7. Department
    a. Bank supervision
    b. Policy
    c. IT
    d. Support
    e. Other please specify

APPENDIX B

Wits Business School University of the Witwatersrand

PARTICIPANT INFORMATION SHEET

Dear Sir / Madam,

My name is Sibusiso Kunene, I am a Masters student in the Faculty Commerce, Law and Management at the University of the Witwatersrand, Johannesburg, currently studying towards an MBA. My current research study is titled “The factors influencing the adoption of ML for bank regulation by Central Banks in SADC Region”

I am conducting a research study about the factors influencing the adoption of ML and Central Banks in the Southern African Development Community (SADC) region will continue to face numerous challenges related to technology disruption and their role will require a significant transformation of their technological capabilities and strategy to ensure relevance in the digital era. This research topic aims to gain insight into the factors influencing the adoption of ML technologies by central banks within the SADC region and the need to understand the problems and opportunities related to the use of ML tools in the regulatory environment.

Participation in this study is entirely voluntary. The survey will be completely confidential and anonymous with no questions seeking identifying information, and the results will be used for academic purposes only.

You have the right to withdraw at any time without providing a reason, and your decision to participate or not will not affect your relationship with Wits Business School or any affiliated organisations.

To achieve the purpose and meet the objectives of this study, I am inviting you to take part in answering a questionnaire. If you would like to participate, your participation in the study will last between 10 and 15 minutes.

Your participation would not only improve the representation of my findings but also assist in my quest to contribute to the body of knowledge. If you would like to participate, please click on the link below: https://wits.eu.qualtrics.com/jfe/form/SV_3fLbEN8lNGRBU3k

If you have any questions during or afterward about this research study, feel free to contact the researcher or the supervisor at the details listed below. 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 hrecnonmedical@wits.ac.za.

Researcher: Mr Sibusiso Kunene

Email : 2506503@students.wits.ac.za

Contact details : 072 089 0628

Supervisor: Dr Jacques Totowa

Email : jacques.totowa@wits.ac.za

Contact details : 011 717 4853

Annexure C

Wits Business School

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Wits Business School

University of the Witwatersrand

Consent Form

Title of project: The factors influencing the adoption of ML for bank regulation by central banks in SADC region.

Name of researcher Sibusiso Kunene

I, ……………………………………….., agree to participate in this research project.

I agree to the following:

(Please circle the relevant options below)

The research study was explained to me. I understand what this study is about.	YES	NO
I understand that I can volunteer to take part in the study	YES	NO

I agree that I am authorised to give information about the company and no confidential information will be put in the survey and shared.	YES	NO
I agree that my participation will remain anonymous (my name or other identifying data will not be used by the researcher in their research report/manuscript/book chapter)	YES	NO
I agree that other researchers may use the information I provide in my interview/focus group/other activity (depending on their own ethics clearance being obtained) but my name and any personal information will not be used or passed on.	YES	NO

……………………………………. (signature)
……………………………………. (name of participant)
……………………………………. (date)

Kunene S.R………………… (signature)
Sibusiso………………………… (name of researcher)

Thank you for your participation.

Annexure D

Ethical Clearance

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

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

Ethics Clearance Certificate

Ethics protocol number: WBS/BA2506503/326
This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	The factors influencing the adoption of machine learning for regulation by central banks in SADC
Investigator / Researcher	Mr Sibusiso Kunene
Nature of Project	MBA (Research Article)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	9/11/2023
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

13/09/2023
Date:

Annexure E

Approved Topic

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Private Bag 3 Wits, 2050
Fax:
Tel:

Reference: Ms Jennifer Mgolodela
E-mail: jennifer.mgolodela@wits.ac.za

30 January 2024
Person No: 2506503
PAG

Mr S Kunene
94 Van Deventer road
Pierre van ryneveld
Pierre Van Ryneveld
0157
South Africa

Dear Mr Sibusiso Kunene

Master of Business Administration: Approval of Title

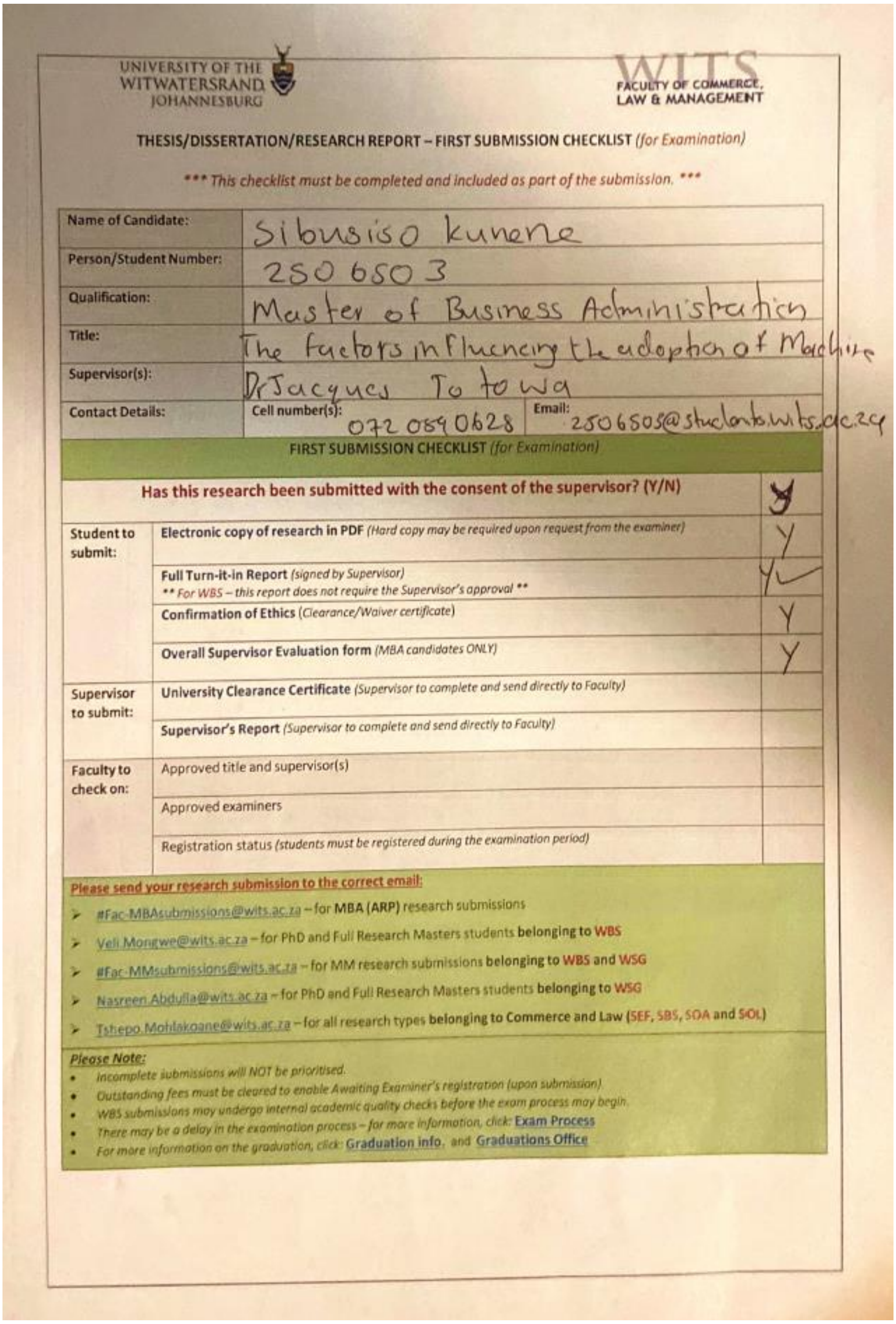
We have pleasure in advising that your proposal entitled *The factors influencing the adoption of machine learning for regulation by central banks in SADC* has been approved. Please note that any amendments to this title have to be endorsed by the Faculty's higher degrees committee and formally approved.

Yours sincerely

Mrs Marike Bosman
Faculty Registrar
Faculty of Commerce, Law and Management

Annexure F

Checklist



UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

WITS FACULTY OF COMMERCE, LAW & MANAGEMENT

THESIS/DISSERTATION/RESEARCH REPORT – FIRST SUBMISSION CHECKLIST *(for Examination)*

**** This checklist must be completed and included as part of the submission. ****

Name of Candidate:	Sibusiso kunene
Person/Student Number:	2506503
Qualification:	Master of Business Administration
Title:	The factors influencing the adoption of Machine
Supervisor(s):	Dr Jacques Totowa
Contact Details:	Cell number(s): 072 059 0628 Email: 2506505@students.wits.ac.za

FIRST SUBMISSION CHECKLIST *(for Examination)*

	Has this research been submitted with the consent of the supervisor? (Y/N)	Y
Student to submit:	**Electronic copy of research in PDF** *(Hard copy may be required upon request from the examiner)*	Y
	Full Turn-it-in Report *(signed by Supervisor)* *** For WBS – this report does not require the Supervisor's approval ***	Y
	Confirmation of Ethics *(Clearance/Waiver certificate)*	Y
	Overall Supervisor Evaluation form *(MBA candidates ONLY)*	Y
Supervisor to submit:	**University Clearance Certificate** *(Supervisor to complete and send directly to Faculty)*	
	Supervisor's Report *(Supervisor to complete and send directly to Faculty)*	
Faculty to check on:	Approved title and supervisor(s)	
	Approved examiners	
	Registration status *(students must be registered during the examination period)*	

Please send your research submission to the correct email:

- #Fac-MBAsubmissions@wits.ac.za – for **MBA (ARP)** research submissions
- Veli.Mongwe@wits.ac.za – for PhD and Full Research Masters students **belonging to WBS**
- #Fac-MMsubmissions@wits.ac.za – for MM research submissions **belonging to WBS and WSG**
- Nasreen.Abdulla@wits.ac.za – for PhD and Full Research Masters students **belonging to WSG**
- Tshepo.Mohlakoane@wits.ac.za – for all research types **belonging to Commerce and Law (SEF, SBS, SOA and SOL)**

Please Note:

- *Incomplete submissions will NOT be prioritised.*
- *Outstanding fees must be cleared to enable Awaiting Examiner's registration (upon submission).*
- *WBS submissions may undergo internal academic quality checks before the exam process may begin.*
- *There may be a delay in the examination process – for more information, click:* Exam Process
- *For more information on the graduation, click:* Graduation info, and Graduations Office

Annexure G

Turnitin