The adoption of AI for project portfolio management in South African financial services

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Supervisor: Mr Mitchell Hughes

DECLARATION

I hereby declare that this research report is my original work. It is submitted as part of the requirements for the Master of Management in Digital Business degree at the University of the Witwatersrand, Johannesburg.

This work has not been submitted previously for any degree or examination at this or any other institution.

Kundishora Chisuro

Signed at Broadacres

Date: 28 May 2025

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I am deeply grateful to my supervisor, Mitchell Hughes for his invaluable support, guidance and professionalism that made this journey smoother and more enriching. I could not have been paired with a better supervisor.

To my niece Lindokuhle and my day one, Simba, thank you for showing up in countless ways, always!

I am also grateful to the village that is my friends, my extended family and all the respondents who generously shared their insights and experiences, contributing to the success of this study.

Above all, I thank God for His infinite grace.

DEDICATION

This work is dedicated to my amazing son, Atida Thebeyarona, without whom my life would have no meaning. I love you and always remember to be kind; it costs nothing.

I also dedicate it to my family.

To my father, Andrew Kativu, who instilled in me from an early age the values of discipline and hard work and always reminded me that “life is what you make it”. To my loving mother, Concepta Gadzai, whose beautiful heart and gentle spirit nurtured me with kindness and whose endless prayers have uplifted and guided me throughout my life. To my elder brother, Zvikomborero, the unspoken pillar of strength in our family - a man blessed beyond measure. And to my younger brother, Tawanda, whom I will love forever.

ABSTRACT

The growing potential of artificial intelligence (AI) to improve project portfolio management (PPM) through better decision making, resource optimisation and strategic alignment is creating new opportunities for the South African financial services sector. This study examines the key technological, organisational and environmental factors influencing the adoption of AI for PPM, filling an important gap in research on emerging markets. Using the Technology-Organisation-Environment (TOE) framework, the study adopts a quantitative, cross-sectional design. Based on a literature review, nine key factors were identified and included in a questionnaire to assess their importance. The data was collected from IT and project management employees in South African financial services organisations. Covariance-based structural equation modelling (CB-SEM) was used to analyse the relationships between these factors and the adoption of AI. The results show that high data quality and a favourable investment environment are the most important factors. Organisational readiness, technological infrastructure, top management support, supportive culture and government regulation also have a positive influence. In contrast, the availability of AI technologies and skilled technical personnel has a negative effect when considered alone, suggesting that these factors may hinder adoption without additional support. Although the study focuses on the South African financial services sector, which may limit the generalisability of the findings, it provides useful insights into the factors driving AI adoption. The findings provide recommendations for financial organisations, IT leaders, project management stakeholders and policy makers to support AI integration, guide strategic decisions and develop frameworks that promote responsible AI adoption while driving innovation. This research contributes to the theoretical understanding of AI adoption for PPM in emerging markets, particularly in South Africa. By applying the TOE framework and CB-SEM, it highlights the importance of an integrated approach considering the interplay of technological, organisational and environmental factors.

Keywords: artificial intelligence, adoption, financial services, project portfolio management, technology-organisation-environment (TOE) framework, structural equation modelling

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LIST OF ACRONYMS

AI	Artificial intelligence
AVE	Average variance extracted
CB-SEM	Covariance-based structural equation modelling
CFA	Confirmatory factor analysis
CFI	Comparative fit index
CR	Composite reliability
DOI	Diffusion of innovation
EFA	Exploratory factor analysis
FS	Financial services
GFI	Goodness-of-fit index
HTMT	Heterotrait-monotrait ratio
ICT	Information and communication technologies
IFI	Incremental fit index
LLMs	Large language models
ML	Machine learning
NLP	Natural language processing
PCA	Principal component analysis
PLS-SEM	Partial least squares structural equation modelling
PMI	Project management institute
POPIA	Protection of Personal Information Act
PPM	Project portfolio management
RMSEA	Root mean square error of approximation
RPA	Robotic process automation
ROI	Return on investment
RQ	Research question
SARB	South African Reserve Bank
SEM	Structural equation modelling
TAM	Technology acceptance model
TPB	Theory of planned behaviour
TOE	Technology-organisation-environment
TLI	Tucker-Lewis index
TPB	Theory of planned behaviour
UTAUT	Unified theory of acceptance and use of technology

CHAPTER 1. INTRODUCTION

1.1 Background

Since 2010, the financial services industry in South Africa has transformed and entered a digital marathon, a journey that has evolved and taken organisations through several stages of digitalisation (Kumari et al., 2024; Ajigini and Chinamasa, 2023; Modiba and Kekwaletswe, 2021; Deloitte, 2022; Oliver Wyman, 2024). Technological advances and the increasing demand for efficient, personalised services have driven the change in the industry. A key technological development impacting this sector globally is AI (Schoeman et al., 2021; Matsepe and Van Der Lingen, 2022; Costa et al., 2022).

AI brings advanced analytical capabilities that enable a better understanding of data, trends and patterns in the project environment (Čančer et al., 2023; Light, 2024; Kestenholz, 2023; Oyekunle et al., 2024). It enables financial service providers to completely redefine the way they work, how they develop innovative products and services and how they transform the customer experience (Kumari et al., 2024).

PMI (2023) and Silvius and Marnewick (2022) highlight the importance of project portfolio management (PPM) in selecting, evaluating and prioritising projects that align with strategy, helping organisations perform better. The arrival of AI has created a capability that organisations can build on. According to PMI (2023), 21% of respondents to a global project management survey said they always or often use AI in managing projects. In comparison, 82% of executives say AI will have at least some impact on how projects are delivered in their organisation in the next five years.

Interest in AI among South Africans has grown by 370% over the past year and by 650% over the last five years (IT Web, 2024). Furthermore, 91% of South Africans believe that life with AI will be significantly different five years from now (IT Web, 2024). South Africa's unique economic and technological environment presents both opportunities and challenges for adopting AI for PPM in financial services.

South Africa also faces challenges such as economic inequality, organisational resistance, a shortage of skilled labour in high-tech fields and varying levels of technological infrastructure across the country (Schoeman et al., 2021).

These factors influence how AI technologies are accepted and implemented in the industry (Matsepe and Van Der Lingen, 2022). Despite these challenges, there is growing momentum among South African financial institutions to adopt AI in order to remain competitive and meet regulatory requirements (Gaffley, 2021). The use of AI for PPM in the South African financial services sector is evident in various initiatives and pilot projects by leading banks such as Standard Bank and FirstRand, which have invested in AI-driven platforms to improve their project management capabilities. In addition, government and regulatory bodies in South Africa, such as the South African Reserve Bank, are increasingly supporting the integration of AI into financial services (SARB, 2020).

Despite the opportunities arising from the implementation of AI applications, research on the operational factors driving the adoption of AI in the financial sector is very limited (Kumari et al., 2024; Matsepe and Van Der Lingen, 2022). While global studies highlight AI's transformative potential in financial services, little specific research exists on its application in PPM in South Africa. More localised research is needed to address these unique conditions and provide insights to help South African financial service providers effectively leverage AI for strategic project management.

1.2 Research problem

Despite big advances in AI technologies and their benefits in various industries, the financial services sector in South Africa has been slow to adopt AI-powered PPM solutions. The application of AI for PPM in the South African financial services sector is still underexplored and presents an opportunity to improve operational efficiency, strategic alignment and better return on investment (ROI). However, integrating AI into PPM processes encounters several challenges and gaps that must be addressed.

Despite global advances, the South African financial services sector has been slow to adopt AI-powered PPM, limiting opportunities for improved efficiency and strategic alignment. This delay hinders competitiveness and ROI in a fast-paced, data-driven environment. Understanding the technological, organisational, and environmental barriers is essential to unlock AI’s full potential in this sector

This research will focus on three critical dimensions: technological factors, organisational factors and environmental factors. Each dimension is essential for understanding the multifaceted nature of AI adoption for PPM within the financial services sector in South Africa.

1.3 Purpose of the study

This study uses the technology-organisation-environment (TOE) framework to identify the factors that affect the adoption of AI for PPM in South African financial services.

This study seeks to answer the following four research questions (RQ):

RQ1: What technological factors affect the adoption of AI for PPM in South African financial services?

Understanding technological factors is crucial as they directly influence the implementation and functionality of AI systems. This includes assessing the availability and maturity of AI technologies, compatibility with existing systems, data quality and infrastructure. Identifying these factors helps recognise the technological readiness and barriers that may impact AI adoption for PPM.

RQ2: What organisational factors affect the adoption of AI for PPM in South African financial services?

Organisational factors such as leadership support, company culture, and employee skill levels play a big role in adopting new technologies. By examining these factors, the study aims to uncover how organisational readiness, strategic priorities and internal capabilities influence the decision to adopt AI for PPM. This understanding can guide organisations in preparing for successful AI integration.

RQ3: What environmental factors affect the adoption of AI for PPM in South African financial services?

Environmental factors include external elements such as regulatory frameworks, market competition and economic conditions. These factors can either facilitate or hinder the adoption of AI technologies. Exploring these elements provides insights into the broader context within which financial services operate and how external pressures and opportunities impact AI adoption decisions.

RQ4: To what extent do these technological, organisational and environmental factors affect the adoption of AI for PPM in South African financial services?

This question aims to quantify and compare the impact of technological, organisational and environmental factors on AI adoption for PPM in financial services in South Africa. Understanding the extent to which each factor influences the adoption process helps identify the most critical areas that need attention. This comprehensive analysis can inform strategic planning and policymaking to support the effective implementation of AI for PPM within the financial sector.

1.4 Intended contribution of the study

1.4.1 Academic contribution

This study has the potential to enhance academic understanding by addressing the current gap in the literature on the adoption of AI for PPM in South Africa's financial services sector. Existing studies on AI adoption have often been generalised or concentrated on developed economies, with limited focus on emerging markets, particularly within the South African context (Schoeman and Seymour, 2022; Kumari et al., 2024; Matsepe and Van Der Lingen, 2022). By utilising theoretical frameworks on technology adoption, specifically the TOE framework by Tornatzky and Fleischer (1990), this study will examine the factors influencing AI adoption for PPM. The findings have the potential to contribute to the broader discussion on technology adoption within financial services, offering nuanced insights into the interplay of regional economic, social and organisational factors unique to South Africa (Badghish and Soomro, 2024; Costa et al., 2022; Gupta et al., 2022).

1.4.2 Contextual contribution

In the context of South Africa, this research has the potential to shed light on the unique technological, organisational and environmental factors that influence the adoption of AI in financial services. A company's organisational environment consists of its resources, like its technological infrastructure and professional workforce, as well as its size, scope, working culture, communication methods and managerial structure (Srinivasan et al., 2024). The South African financial sector is characterised by advanced institutions alongside significant disparities in technological infrastructure and skills availability (Kumari et al., 2024; F. Schoeman and Seymour, 2022). By examining these contextual factors, the study aims to contribute to a deeper understanding of the South African characteristics that influence AI integration. This contextual analysis has the potential to provide a critical foundation for the development of localised strategies that can effectively address the barriers to AI adoption in the South African financial services sector.

1.4.3 Practical contribution

From a practical perspective, this study can provide valuable insights and recommendations for financial institutions in South Africa seeking to adopt AI in their PPM processes. By identifying key factors influencing AI adoption, the study has the potential to offer targeted strategies to overcome existing barriers. PPM has evolved in line with the new digital reality and now comprises four core functions: Portfolio Management, Demand Management, Project or Solution Management and Business Outcome Management (Deloitte, 2020). McKinsey and Company (2023) emphasises that active portfolio management is critical for aligning projects with strategic objectives and maximising value creation. Furthermore, documenting case studies on the successful implementation of AI within South Africa's financial services sector can highlight best practices and lessons learned, providing practical guidance for institutions aiming to enhance project management efficiency and decision-making processes. Additionally, the findings can assist policymakers and regulators in developing supportive frameworks for AI integration, promoting innovation and competitiveness within South Africa's financial services industry.

1.5 Delimitations of the study

a. The study will have a geographical focus specifically on financial institutions within South Africa, excluding comparisons with other countries or regions.
b. The study will have a sectoral focus exclusively on the financial services industry, excluding other sectors such as telecommunications or manufacturing.
c. The study will have a temporal focus on examining trends and drivers of AI adoption up to the present day, excluding future projections or historical analyses beyond the last decade.
d. The study will have a technological scope primarily focused on AI technologies that include ML, NLP, LLM and expert systems related to PPM processes, excluding broader applications of AI in the financial services sector that are unrelated to PPM.
e. The study will have a sampling focus that includes a specific sample size and selection criteria for financial institutions in South Africa, excluding smaller or unrepresentative companies that may not reflect broader industry trends.

1.6 Assumptions of the study

a. Respondents will reflect standard perspectives and experiences in their respective organisations. It can be assumed that respondents, typically senior executives, project managers, or IT employees involved in AI adoption, will provide insights based on their roles and experience in their organisations.
b. The TOE framework adequately captures the key factors affecting the adoption of AI for PPM in South African financial services. It is widely recognised in technology adoption research and provides a structured

approach to understanding the relationship between technological, organisational and environmental factors.

c. Financial institutions in South Africa are actively seeking to improve operational efficiency using AI for PPM. Given global trends and competitive pressures, it is reasonable to assume that they are motivated to use AI to improve PPM processes and maintain competitiveness.

1.7 Definition of terms

a. *Adoption:* Adoption refers to the process through which individuals, organisations, or industries accept, integrate and utilise new technologies, practices, or innovations. It involves stages such as awareness, evaluation, trial and implementation, influenced by factors like perceived usefulness, organisational readiness and external environmental conditions (Gupta et al., 2022; Tornatzky and Fleischer, 1990; Kumari et al., 2024).
b. *Artificial Intelligence (AI):* AI is defined as the simulation of human intelligence by machines (programs) through the use of various technologies like deep learning, machine learning, data mining, image recognition, natural language processing and more (Badghish and Soomro, 2024).
c. *Financial Services (FS):* The financial sector is a segment of the economy consisting of companies and institutions that offer financial services to commercial and retail clients, encompassing a wide array of industries, including banks, investment companies, insurance companies and real estate businesses (Kenton, 2021).
d. *Project Portfolio Management (PPM):* PPM involves the centralised management of one or more portfolios, including the processes of identifying, prioritising, authorising, managing and controlling projects, programmes and related work to achieve specific strategic business objectives (Adams, 2020; Pajares and López, 2014; Silvius and Marnewick, 2022; Teller et al., 2012; Deloitte, 2020; Martinsuo and Geraldi, 2020).

e. *Structural Equation Modelling (SEM):* SEM is a multivariate statistical analysis technique used to analyse structural relationships between measured variables and latent constructs. It combines factor analysis and multiple regression analysis to assess complex cause-and-effect relationships, making it a powerful tool for testing theoretical models and hypotheses in research (Hair et al., 2019; Byrne, 2016; Kline, 2016).
f. *Technology-Organisation-Environment (TOE):* The TOE framework offers a thorough approach to analysing how technology characteristics, organisational factors and environmental influences interact to shape organisational adoption decisions (Badghish and Soomro, 2024; Baker, 2012; Maragno et al., 2023; Rjab et al., 2023; Srinivasan et al., 2024; Yang et al., 2024).

1.8 Structure of the report

This chapter explains the background of the research on adopting AI for PPM in the South African financial services sector. The research problem is divided into three sub-questions to identify technological, organisational and environmental factors in adopting AI for PPM. The contributions of this study have also been categorised into academic, contextual and practical aspects. The rest of this study is structured and unpacked in the following chapters:

Chapter 2: Literature Review and Theoretical Framework

This chapter provides a literature review that focuses on the three dimensions of the research: technological factors, organisational factors and environmental factors. It also discusses the theoretical foundations of the proposed TOE framework and develops the research model used in this study. A contextual diagram of AI adoption for PPM, including the individual constructs and factors, is presented. The chapter concludes with the development of the proposed hypotheses to be tested.

Chapter 3: Research Methodology

This chapter provides an overview of the quantitative research design and data collection methodology used in this study to answer Research Question 1 (RQ1) to explore technological factors for AI adoption; Research Question 2 (RQ2) to examine organisational factors contributing to AI adoption; and Research Question 3 (RQ3) to understand key environmental factors for AI adoption; and Research Question 4 (RQ4) to understand the combined effect of all TOE factors.

Chapter 4: Presentation of Results

This chapter presents the results of South African financial services organisations' adoption of AI for PPM, mapped to the TOE constructs. The data is analysed and conclusions on hypotheses are drawn.

Chapter 5: Discussion of Results

This chapter presents a detailed analytical discussion of the data analysis results on hypothesis testing and references to the literature evaluated in earlier chapters.

Chapter 6: Conclusion and Recommendations

This chapter discusses the results of adopting AI for PPM and describes the findings for academic, contextual and practical application for South African financial services. It also outlines the study’s limitations and identifies potential areas for future research.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

The rapid development of AI technologies has opened up significant opportunities for the financial services industry to optimise various processes, including PPM (Nieto-Rodriguez and Vargas, 2023; PMI, 2023). The potential of AI to improve decision making, optimise resource allocation and increase overall efficiency and productivity makes it an attractive solution for managing organisational complexity (Baabdullah, 2024; Badghish and Soomro, 2024; Costa et al., 2022; Pajares and López, 2014; Solaimani and Swaak, 2023).This literature review aims to explore the adoption of AI for PPM in the South African financial sector, where unique challenges and opportunities arise.

This study contributes to the literature by employing a framework that categorises the drivers for AI adoption based on the TOE model developed by Tornatzky and Fleischer (1990). Rjab (2023) states that adopting information and communication technologies (ICT) involves the full utilisation of the technology through its integration, implementation and use, but adopting AI technologies requires more research due to its relatively new and not fully understood nature. In addition, the importance of project management in AI-driven environments has increased as AI technologies are critical to organisations in various industries. Previous studies have explored how organisations are using these AI technologies to drive innovation, improve efficiency and gain competitive advantage (Oyekunle et al., 2024; Schoeman et al., 2021).

To provide a comprehensive analysis, this literature review will be guided by the following research dimensions:

a. Technological factors that affect the adoption of AI for PPM in South African financial services.
b. Organisational factors that affect the adoption of AI for PPM in South African financial services.
c. Environmental factors that affect the adoption of AI for PPM in South African financial services.

This study aims to provide a clear understanding of the current state of AI adoption for PPM in the South African financial services industry by exploring key dimensions, identifying drivers and barriers, and offering recommendations.

2.1.1 Definition of artificial intelligence (AI)

Artificial intelligence (AI) is a multidisciplinary field that integrates computer science and advanced algorithms to enable machines to perceive, learn from and interact with their environment autonomously (Kumari et al., 2024; Solaimani and Swaak, 2023). AI technologies include various subfields such as machine learning (ML), machine vision, natural language processing (NLP), expert systems, robotics, language processing and evolutionary computation (Solaimani and Swaak, 2023; Yang et al., 2024). A seminal study by McCarthy et al. (1955) established the basic principles of AI and defined it as the science and technology of developing intelligent machines.

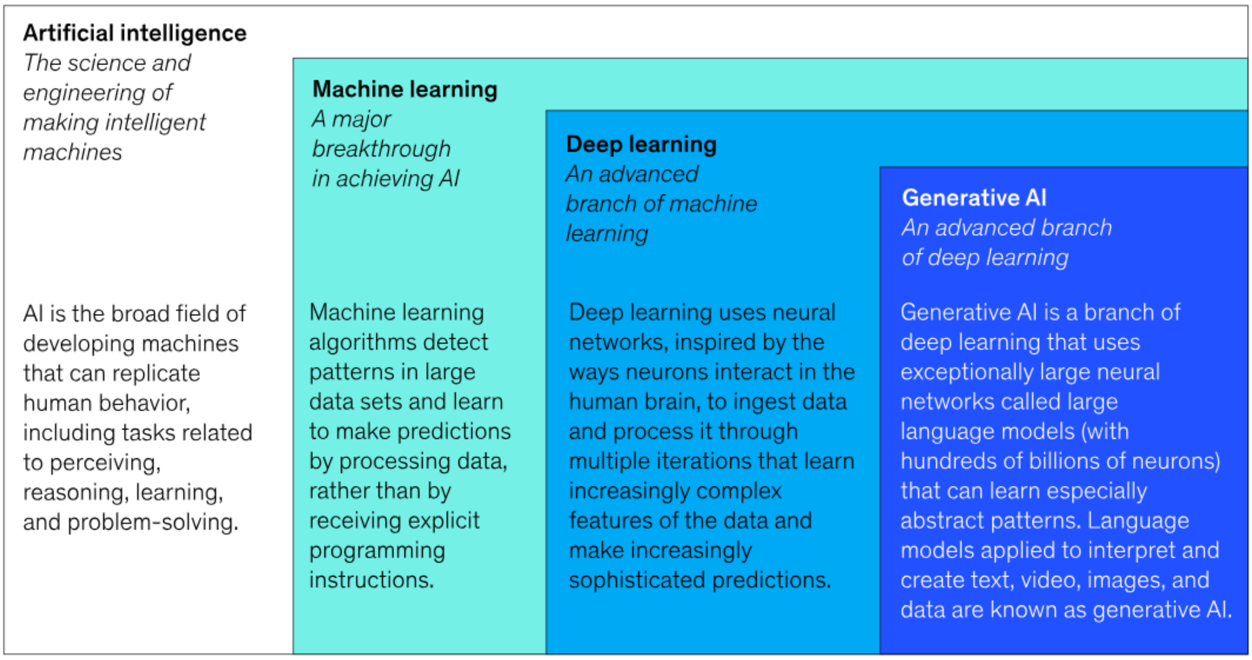

Figure 1. The evolution of AI (McKinsey and Company, 2024)

Figure 1 illustrates the evolution of AI and its subsets, including machine learning, deep learning and generative AI (McKinsey and Company, 2024).

2.1.2 Definition of project portfolio management (PPM)

Project portfolio management (PPM) involves the centralised management of one or more portfolios, including the processes of identifying, prioritising, authorising, managing and controlling projects, programmes and related work to achieve specific strategic business objectives (Adams, 2020; Pajares and López, 2014; Silvius and Marnewick, 2022; Teller et al., 2012; Deloitte, 2020; Martinsuo and Geraldi, 2020). PPM serves as a crucial link between an organisation's strategic goals and its operational measures and ensures alignment between projects and the overarching strategy (Silvius and Marnewick, 2022; Pajares and López, 2014; Teller et al., 2012).

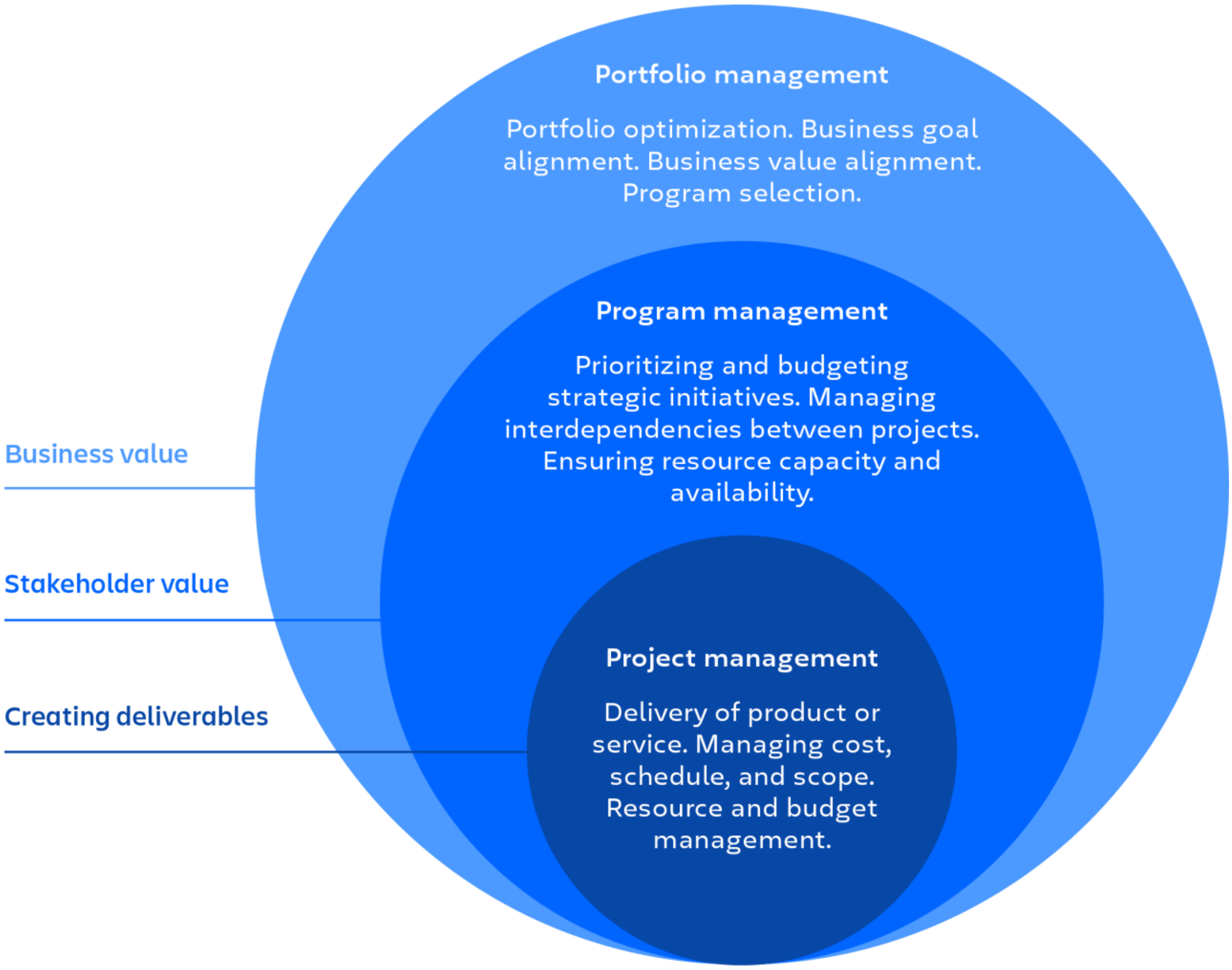

Figure 2. Project, programme and portfolio management (Mallek, 2024)

Martinsuo and Geraldi's (2020) research shows that PPM encompasses resource allocation, project interdependencies, formal project selection and control governance and decision-making processes. PPM increases organisational efficiency by aligning projects with corporate strategy, ensuring rational resource allocation and achieving greater efficiency than managing projects separately (Martinsuo and Geraldi, 2020; Pajares and López, 2014). This strategic approach enables organisations to renew and implement their strategies dynamically, adapting to evolving business environments and achieving substantial strategic benefits.

2.2 Current state of AI adoption in financial services

Global perspective

Building upon the work of Johnson (2018), this review explores the advancements in AI adoption within the financial services sector, driven by the promise of enhanced efficiency and cost savings. Technologies like NLP, ML and virtual assistants are widely integrated to optimise processes and improve decision making. Using large language models (LLMs) such as ChatGPT exemplifies this trend, offering substantial benefits but presenting challenges such as corporate data leakage risks. Managing these risks through clear usage policies and training is essential to realise AI's potential fully (Norton Rose Fulbright, 2023). Despite these advancements, recent studies reveal that over half of AI projects do not deliver the expected outcomes (Yang et al., 2024). Effective management and strategic alignment are crucial for successful AI adoption.

According to a global survey on AI by McKinsey (2024), interest in generative AI has highlighted a wider range of AI capabilities. Over the past six years, AI adoption in respondents' organisations remained around 50%. No region achieved a 66% adoption rate; however, in 2023, over two-thirds of respondents in every region reported that their organisations were utilising AI. Additionally, responses indicate that companies are now applying AI across more business areas.

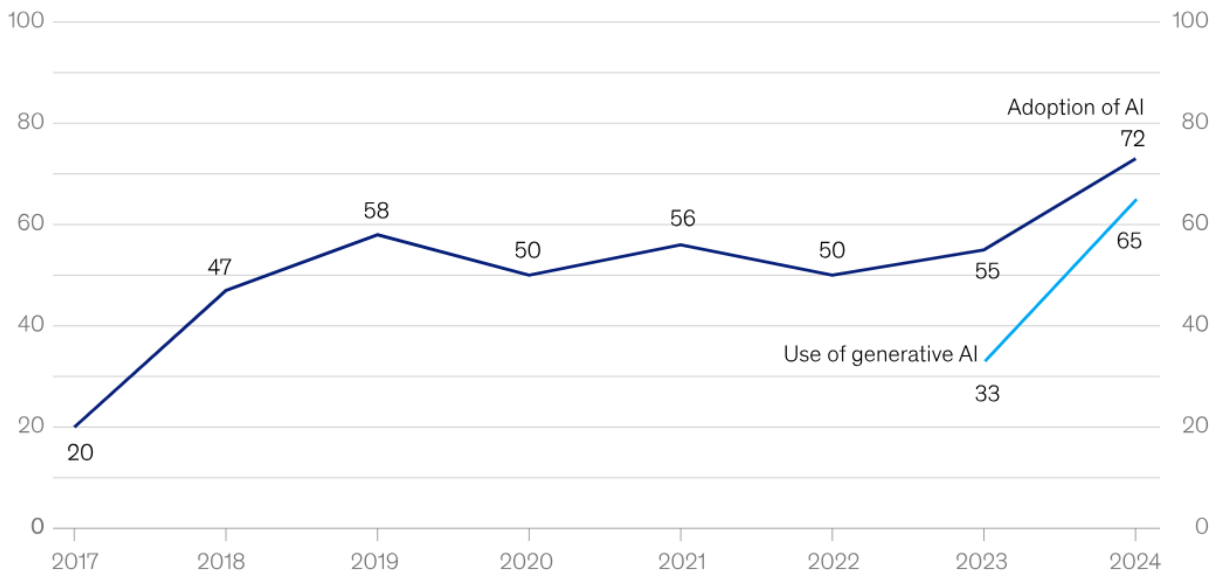

Figure 3. Organisations that have adopted AI in at least one business function (McKinsey, 2024)

A global survey by The Economist (2022) indicates that AI adoption in financial services progresses as banks deploy it across various innovative applications. The survey reveals that 85% of IT executives in banking have a well-defined strategy for integrating AI in developing new products and services. The emergence of portfolio optimisation in the Top 3 of executives' plans to use the technology in the next three years supports the need for this study where AI adoption for PPM is relevant and an emerging phenomenon.

AI's role in continuous innovation, which is essential in the current business environment, is seen through research that links AI-driven innovation with improved financial performance, helping organisations address both business and societal goals (Lappalainen et al., 2023). However, despite extensive research on AI benefits, gaps remain in the literature regarding the challenges businesses must navigate to fully realise these benefits. Further studies are needed to generalise these findings across different regions and explore the long-term impacts of AI on workforce dynamics and productivity.

South African context

The South African Reserve Bank has proactively fostered digital innovation, establishing a fintech unit in 2017 to drive technological advancements and create innovation-friendly structures (SARB, 2020). This regulatory support is crucial for fostering an environment conducive to AI integration and highlights the importance of policy frameworks in promoting technological adoption (Oliver Wyman, 2024). However, despite these efforts, the financial sector faces significant barriers, such as legacy technologies, outdated business models and concerns about job displacement and income inequality (Schoeman et al., 2021). These challenges underscore the need for further research to develop strategies that mitigate socio-economic impacts and enhance workforce readiness for AI.

Despite extensive research on the transformative potential of AI, there remain gaps in the literature regarding the practical implementation and real-world outcomes of AI technologies in South Africa. This review addresses a notable gap by examining the specific benefits and challenges South African financial institutions face. AI has been shown to enhance planning, forecasting and overall business operations, reducing costs and increasing revenues through improved product quality and marketing strategies (Costa et al., 2022). However, the integration of AI into existing business processes remains complex, often falling short of expected outcomes due to the dynamic and disruptive nature of AI (Yang et al., 2024).

Financial institutions are leveraging AI to deliver personalised experiences and on-demand banking, driven by the need to stay competitive amidst rising challenges from neobanks and big tech companies (Oliver Wyman, 2024). Most executives agree that AI will revolutionise customer interactions and improve business operations, but only about a third of South African organisations plan sizeable AI investments over the next three years (Moore et al., 2021). This holistic view underscores the importance of continuous investment in AI and related technologies in South Africa.

2.3 Role of AI in PPM

2.3.1 Enhancing decision making

Building upon the work of Badghish and Soomro (2024) and Solaimani and Swaak (2023), AI significantly enhances business performance by improving decision making through advanced data analytics and predictive capabilities. Following the insights of Solaimani and Swaak (2023) and Oyekunle et al. (2024), the growing reliance on AI-driven solutions such as intelligent automation and cognitive augmentation underscores the transformative potential of AI for PPM. Recent studies reveal that over half of AI projects do not deliver the expected outcomes, often due to AI's dynamic and disruptive nature that complicates its integration with existing business processes (Norton Rose Fulbright, 2023; Yang et al., 2024).

2.3.2 Optimising resource allocation

AI's transformative potential in financial services is evident in its ability to optimise resource allocation and improve overall business operations. Extending the findings of Deloitte (2020), the enterprise-level adoption of PPM illustrates the growing integration of IT and business practices, which has led to the valuable cross-fertilisation of methodologies. By synthesising findings from Badghish and Soomro (2024) and Solaimani and Swaak (2023), it is clear that AI technologies facilitate this integration by providing advanced data analytics and predictive capabilities that enhance decision-making processes. Despite these benefits, businesses must navigate challenges to fully realise these advantages, highlighting a gap in existing research that often overlooks the practical challenges and solutions associated with aligning IT and business strategies through AI.

2.3.3 Improving efficiency and productivity

AI is fundamentally transforming the financial services industry by leveraging ML technologies to drive internal efficiencies and optimise service delivery (Norton Rose Fulbright, 2023). The emergence of generative AI, based on large language models like ChatGPT, has further accelerated this trend (Norton Rose Fulbright, 2023; Solaimani and Swaak, 2023). Research has shown a positive relationship between formalisation and performance, indicating that structured PPM processes lead to better project outcomes (Silvius and Marnewick, 2022; Teller et al., 2012). However, although Teller et al. (2012) and Silvius and Marnewick (2022) highlighted key aspects of formalisation, additional areas need to be explored, including how formalisation at the project level interacts with formalisation at the portfolio level and how this interaction impacts overall success. Future studies should investigate these dynamics to provide a more comprehensive understanding of formalisation in AI-enabled PPM environments.

2.4 AI application in financial services

AI applications have improved customer service, fraud detection and risk management in the banking sector. For example, FNB's use of AI and ML has saved the bank and its customers over R1.1 billion by enhancing fraud detection and risk management (Malinga, 2024). Similarly, Nedbank's use of Microsoft's Copilot chatbot shows another successful AI implementation. The chatbot assists with various work functions, similar to ChatGPT for Microsoft 365 apps, helping Nedbank streamline processes, mitigate risks, foster innovation and modernise internal tools (Malinga, 2024). Absa has also successfully implemented AI and natural language understanding through its ChatWallet, a WhatsApp-enabled wallet, enhancing customer engagement and service delivery (Msomi, 2024).

Using AI-powered predictive analytics is crucial for improving decision making in PPM. AI algorithms like NLP and ML help project managers forecast risks, identify optimisation areas and make informed decisions by analysing unstructured data sources such as project documentation, emails and meeting transcripts. This leads to better project dynamics and stakeholder sentiment analysis (Oyekunle et al., 2024). AI-assisted cost estimation further automates the cost input process, saving time and increasing accuracy (Kestenholz, 2023).

Organisations can harness AI's potential to enhance decision making, optimise resource allocation and improve efficiency and productivity in PPM, addressing both technical and ethical considerations. Integrating AI into PPM not only streamlines operations but also provides a competitive advantage in today’s data-driven business environment (Taltrics, 2024).

2.5 Conclusion of literature review

The literature review addressed the main research question on the factors that affect the adoption of AI for PPM in the financial services sector in South Africa, using the TOE framework (Baker, 2012). It reveals that AI has the potential to improve decision making, optimise resource allocation and increase PPM efficiency and productivity. However, its adoption can be hindered by technological, organisational and environmental challenges.

These factors are interlinked. Future research should focus on developing empirical evidence on AI's impact on PPM.

2.6 Theoretical framework and hypothesis development

This study explores AI adoption factors grounded in the Technology-Organisation-Environment (TOE) framework. Developed by Tornatzky and Fleischer (1990), the TOE framework provides a holistic perspective on technology adoption and the integration of technology characteristics, organisational factors and environmental influences. This approach is more comprehensive compared to other theories like the diffusion of innovation (DOI) theory, institutional theory and resource-based view, which focus on specific aspects of technology adoption (Baker, 2012). Despite some criticism that the framework's broad categorisation may overlook specific characteristics, its flexibility allows it to adapt to various contexts, making it suitable for studying complex technologies like AI (Baker, 2012; Low et al., 2011). The TOE framework proposes general factors that explain and forecast the likelihood of innovation and technology adoption, making it a robust model for exploring AI adoption in diverse settings (Badghish and Soomro, 2024; Yang et al., 2024). However, compared to theories like the technology acceptance model (TAM), the theory of planned behaviour (TPB) and the unified theory of acceptance and use of technology (UTAUT), which focus on individual decision-making processes, the TOE framework provides a broader, organisational-level perspective (Maragno et al., 2023).

The TOE framework illustrated in Figure 4 is a valuable model for studying AI adoption, offering a comprehensive lens to examine technological, organisational and environmental factors. Its application in numerous studies underscores the critical roles of technological readiness, organisational support and external pressures in facilitating successful technology adoption. While previous research has highlighted its adaptability and broad applicability (Baker, 2012), future research should refine the framework, address its limitations and explore the dynamic interactions between its components to enhance our understanding of technology adoption in rapidly evolving fields like AI.

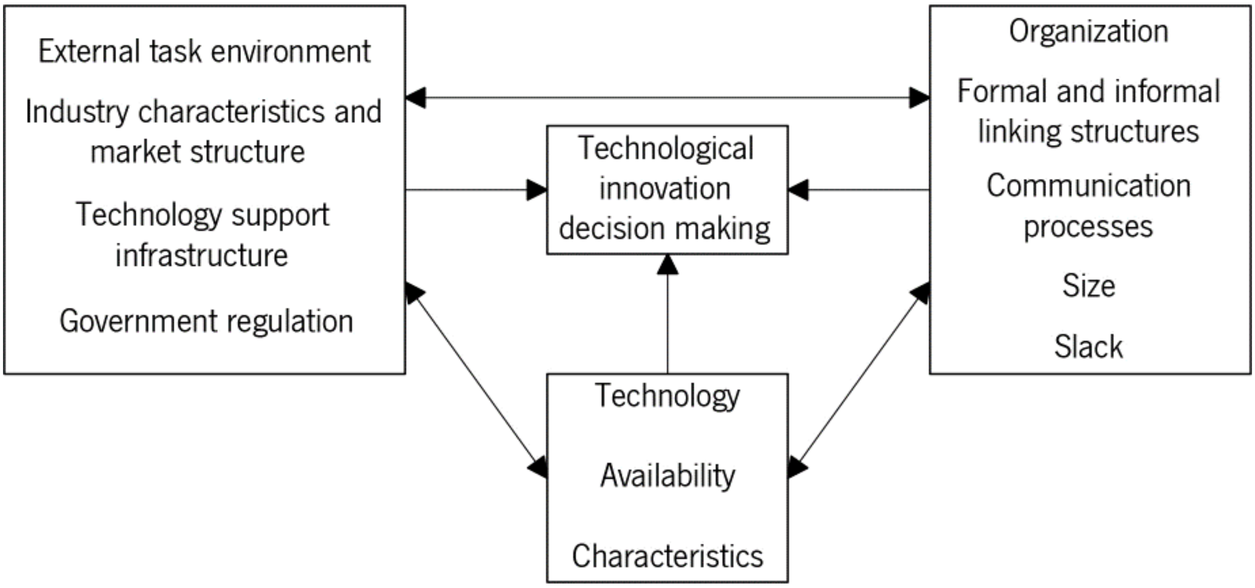

Figure 4. Technology-organisation-environment (TOE) framework (Tornatzky and Fleischer, 1990)

2.6.1 Technological context

The technological context focuses on the technical aspects and infrastructure that influence the adoption of AI for PPM in financial services. This includes the availability, maturity and usability of AI technologies and the quality of data and infrastructure. Advanced and mature AI technologies are crucial for seamless integration into existing systems and effective functioning within the financial sector (Gupta et al., 2022; Kumari et al., 2024) Additionally, the quality of data and the robustness of data infrastructure are critical for the training and operation of AI models (Costa et al., 2022; Gupta et al., 2022). Technologies that are user-friendly and easily integrated into existing workflows are more likely to be adopted (Yang et al., 2024; An et al., 2024).

Availability of AI technologies

The availability of AI technologies is crucial for their adoption within the financial sector. Access to advanced AI technologies can determine how easily organisations can integrate these innovations into their operations (Srinivasan et al., 2024; Kumari et al., 2024; Gupta et al., 2022). Moreover, the breadth and depth of available AI tools and platforms can significantly influence decision-making processes regarding AI investments (Gupta et al., 2022). Therefore, the following hypothesis can be proposed:

H1: *The availability of AI technologies is positively associated with the adoption of AI for PPM in South African financial services.*

Technological infrastructure

A developed technological infrastructure is the key to storing, processing and analysing the large amounts of data required for AI applications. The right infrastructure facilitates the introduction of AI technologies (Costa et al., 2022; Gupta et al., 2022). In addition, sufficient network bandwidth and computing power increase AI's performance and make its implementation more successful.

H2: *The availability of a developed technological infrastructure is positively associated with the adoption of AI for PPM in South African financial services.*

Data quality

High-quality data is essential for the effective training and operation of AI models. High-quality data ensures the accuracy and reliability of AI outputs and the lack of adequate data quality can pose significant challenges to the adoption of AI technologies (Costa et al., 2022; Gupta et al., 2022). Furthermore, data quality issues such as inconsistencies, inaccuracies and biases can undermine AI performance and trust (Salah and Ayyash, 2024). It is hypothesised that:

H3: *High data quality is positively associated with the adoption of AI for PPM in South African financial services.*

2.6.2 Organisational context

The organisational context encompasses the organisational internal dynamics and resources that impact the adoption of AI. This includes top management support, organisational culture and the availability of skilled human resources. Effective top management support and a supportive organisational culture are essential for driving AI initiatives (Costa et al., 2022; Al-Khatib, 2023). Additionally, the availability of skilled human resources proficient in AI and related technologies is crucial for the successful implementation and adoption of AI systems (An et al., 2024; Schoeman and Seymour, 2022; Kumari et al., 2024; Schoeman et al., 2021).

Top management support

Strong support from top management is vital for driving AI initiatives within an organisation. Leaders who understand the potential benefits of AI and are committed to its adoption can secure the necessary resources and advance an innovation culture. Top management support also helps overcome resistance to change and ensures alignment of AI initiatives with the organisation's strategic goals (Nguyen et al., 2022; Costa et al., 2022; Al-Khatib, 2023). Moreover, top management's commitment to resource allocation and strategic direction is crucial for overcoming initial adoption barriers (Nguyen et al., 2022). As a result, this study proposes the following hypothesis:

H4: *Top management support is positively related to the adoption of AI for PPM in South African financial services.*

Availability of skilled AI personnel

Qualified personnel familiar with AI and related technologies are essential for effectively using AI systems. Training and development programmes can help build these skills in the personnel for faster and more successful AI adoption (Kumari et al., 2024; Schoeman et al., 2021). In addition, the availability of AI expertise and managing the cost of hiring skilled labour can significantly facilitate the adoption of AI technologies (Aniceski et al., 2024). As a result, the following hypothesis can be suggested:

H5: *The availability of skilled AI personnel is positively related to the adoption of AI for PPM in South African financial services.*

Organisational culture

A culture that promotes innovation and adaptability is conducive to successfully adopting AI technologies. Organisations that encourage experimentation and are open to change are more likely to integrate AI into their operations effectively. Organisational culture involves having the processes and structures in place to support new technologies and adapt to changes in the business environment (An et al., 2024; Schoeman and Seymour, 2022). Additionally, fostering a culture that values continuous learning and innovation can significantly enhance AI adoption (Salah and Ayyash, 2024). Based on the above arguments, it is proposed that:

H6: *A supportive organisational culture is positively related to the adoption of AI for PPM in South African financial services.*

2.6.3 Environmental context

The environmental context includes external forces such as government regulation, market competition and economic conditions that influence the adoption of AI. Supportive government regulation can facilitate AI adoption by providing necessary guidelines and incentives (Costa et al., 2022; Oliver Wyman, 2024). Market competition drives organisations to adopt innovative technologies to maintain or enhance their market position (Deloitte, 2022; Gupta et al., 2022). Additionally, a stable economic environment and favourable investment conditions are essential for organisations to invest in new technologies (Al-Khatib, 2023; Matsepe and Van Der Lingen, 2022).

Government regulation

Supportive government regulation is crucial for the adoption of AI technologies. Regulations that provide clear guidelines and incentives for AI adoption can encourage organisations to invest in these technologies. Government support can come in the form of funding, tax incentives and the creation of innovation-friendly policies and infrastructure (Oliver Wyman, 2024; Costa et al., 2022; Wang et al., 2024). Furthermore, regulatory frameworks that ensure data privacy and security can enhance organisational trust in adopting AI solutions (Hanna et al., 2020). The following hypothesis can, therefore, be proposed:

H7: *Supportive government regulation is positively associated with the adoption of AI for PPM in South African financial services.*

Market competition

Competitive pressure encourages organisations to adopt innovative technologies to maintain or enhance their market position. In highly competitive markets, organisations are more likely to invest in AI to gain a competitive edge by improving efficiency, reducing costs and enhancing customer experiences (Badghish and Soomro, 2024; Deloitte, 2022). The drive to remain competitive can compel organisations to adopt AI technologies more quickly and effectively (Salah and Ayyash, 2024). This leads to the following hypothesis:

H8: *Increased market competition is positively related to the adoption of AI for PPM in South African financial services.*

Investment conditions

A stable economic environment and favourable investment conditions encourage organisations to invest in new technologies. Economic stability gives organisations the confidence and resources to make significant AI investments. Additionally, a favourable investment climate, including access to capital and supportive financial policies, helps in adopting AI technologies (Dewi and Wiksuana, 2023; Abdurrahman et al., 2024; Matsepe and Van Der Lingen, 2022). Moreover, favourable economic conditions reduce the financial risks associated with AI investments (Mohammad et al., 2022). Therefore, the following hypothesis can be suggested:

H9: *Favourable investment conditions are positively associated with the adoption of AI for PPM in South African financial services.*

Conceptual framework

Figure 5 presents the adapted conceptual framework based on the Technology-Organisation-Environment (TOE) framework, illustrating the key factors influencing AI adoption for PPM. The framework also outlines the study's hypotheses, highlighting the relationships between technological, organisational, and environmental factors.

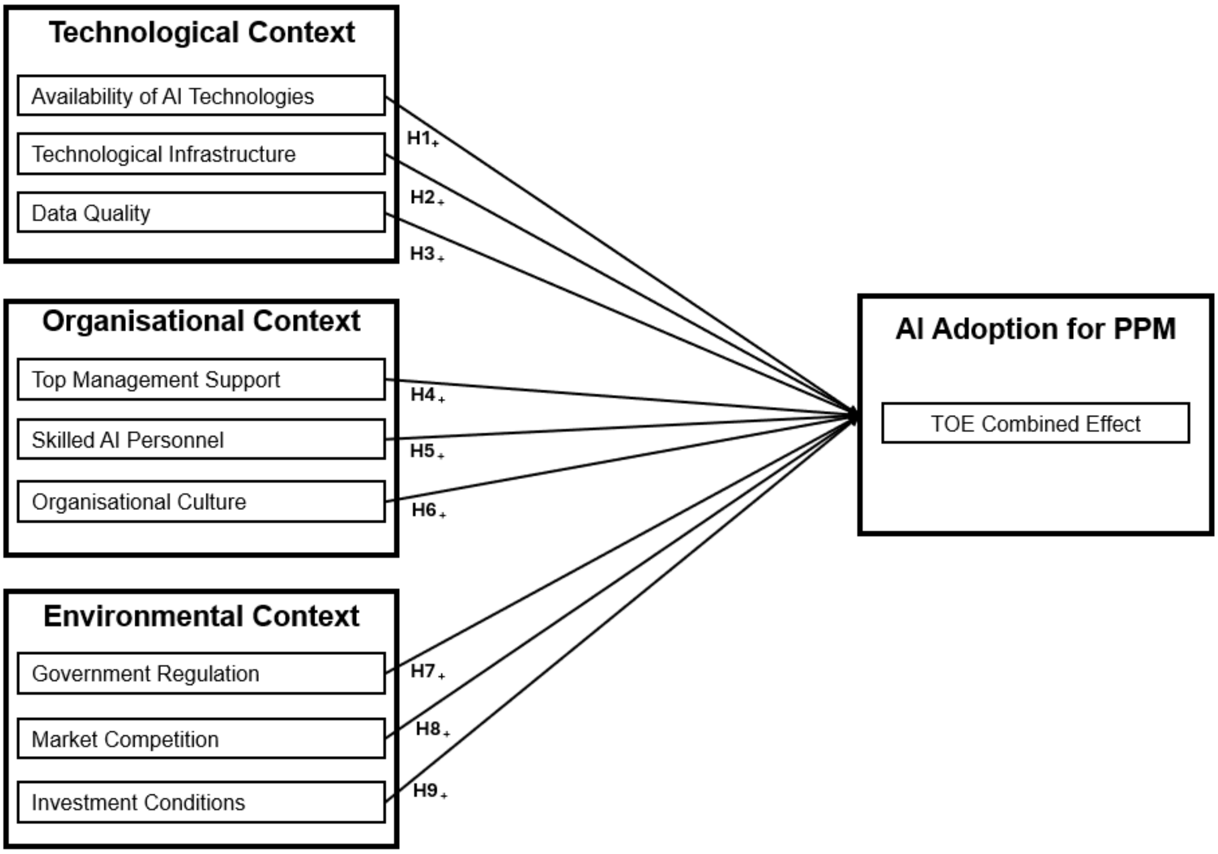

Figure 5. Conceptual framework for the adoption of AI for PPM

Table 1 presents the research hypotheses discussed above, exploring the impact of technological, organisational and environmental factors on AI adoption for PPM within financial services.

Table 1. Summary of research hypotheses

TOE Context	Number	Variable	Research Hypothesis
Technological Context	H1	Availability of AI technologies	The availability of AI technologies is positively associated with the adoption of AI for PPM in South African financial services.
	H2	Technological infrastructure	The availability of a developed technological infrastructure is positively associated with the adoption of AI for PPM in South African financial services.
	H3	Data quality	High data quality is positively associated with the adoption of AI for PPM in South African financial services.

TOE Context	Number	Variable	Research Hypothesis
Organisational Context	H4	Top management support	Top management support is positively related to the adoption of AI for PPM in South African financial services.
	H5	Skilled AI personnel	The availability of skilled AI personnel is positively related to the adoption of AI for PPM in South African financial services.
	H6	Organisational culture	A supportive organisational culture is positively related to the adoption of AI for PPM in South African financial services.
Environmental Context	H7	Government regulation	Supportive government regulation is positively associated with the adoption of AI for PPM in South African financial services.
	H8	Market competition	Increased market competition is positively related to the adoption of AI for PPM in South African financial services.
	H9	Investment conditions	Favourable investment conditions are positively associated with the adoption of AI for PPM in South African financial services.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodology used to examine AI adoption for PPM in South Africa's financial services sector. It provides an overview of the research approach, design, data collection methods and sampling strategy, all aligned with the study's quantitative objectives and the TOE framework. The chapter details the pilot testing process, data analysis techniques, reliability, validity and ethical considerations.

3.2 Research approach

This study used a quantitative research approach because it allows for the collection and analysis of numerical data to uncover patterns, relationships and trends (Bhattacherjee, 2012). This is essential for understanding the factors that affect the adoption of AI for PPM. Quantitative research is grounded in the positivist paradigm, which focuses on empirical evidence and scientific methods to create reliable and generalisable knowledge (Creswell, 2014). This approach was chosen over qualitative methods because it better suits the study's goals of testing hypotheses and identifying trends. While qualitative research is valuable for exploring deep, individual insights, it is also less effective for generating findings that can be applied to large groups (Greener, 2008).

In contrast, quantitative methods allow for data to be collected systematically from a large sample, ensuring that the results represent the broader population (Oates, 2006). Using structured questionnaires ensured consistency and minimised bias, which are critical for producing valid and reliable results (Taherdoost, 2022). Statistical analysis further allowed the study to uncover key relationships between technological, organisational and environmental factors influencing AI adoption. Quantitative research also provides the precision and scalability required to inform policies and strategies for adopting AI in financial services. As Creswell (2014) notes, quantitative methods are particularly suited for studies aiming to answer "what" and "to what extent" questions, making this approach ideal for this research's objectives.

3.3 Research design

The study adopted a cross-sectional survey design, which is widely used in quantitative research to collect data from a large group of people at one point in time (Bhattacherjee, 2012). This design was suitable for examining the views of IT and project management employees in South Africa's financial services sector, as it allowed for efficient collection of data from a diverse group. The survey was conducted using structured questionnaires designed to measure the technological, organisational and environmental factors influencing AI adoption and the impact of AI on PPM. Structured questions ensured that all respondents answered the same questions in the same way, making the data consistent and easy to analyse (Oates, 2006). This approach allowed the study to identify patterns and relationships in the data efficiently (Bhattacherjee, 2012).

Why a survey was chosen over qualitative methods

For several reasons, the survey design was selected over qualitative methods such as interviews or focus groups. First, surveys can cover a much larger sample size, making the findings more representative and generalisable to the broader financial services sector (Bell et al., 2019). Second, surveys are more efficient and cost-effective, especially when distributed electronically, allowing for rapid data collection (Greener, 2008). While qualitative methods can provide richer, more detailed insights, they are typically more time-consuming and less scalable, as described by Cresswell (2014), which made them less suitable for this study's focus on identifying broad patterns and trends.

The survey design's broad reach and generalisability allow data collection from diverse respondents, ensuring findings represent the broader population (Bell et al., 2019). This is particularly relevant in the financial services sector, where organisational and technological contexts vary (Bell et al., 2019). The use of a structured questionnaire also eliminates geographical barriers (Greener, 2008), facilitating participation across South Africa's financial services sector without travel.

Finally, surveys support quantitative analysis techniques, such as regression and factor analysis, providing measurable insights into relationships between variables and enhancing research reliability and validity (Creswell, 2014).

Limitations of the survey design

Despite its advantages, the survey design has limitations. It provides limited depth, as surveys may fail to capture detailed, context-specific insights compared to qualitative methods like interviews (Bhattacherjee, 2012). Additionally, response bias is a concern, as certain groups, such as those familiar with AI, might be more inclined to participate, potentially skewing results. To address this, stratified random sampling and follow-ups were used to ensure diversity and improve response rates (Bell et al., 2019).

Fixed response options in surveys can restrict respondents' ability to express their views fully, limiting data richness and oversimplifying complex issues (Oates, 2006). Furthermore, while electronic surveys are efficient, they rely on respondents' willingness and availability, which can reduce participation, particularly among busy professionals (Greener, 2008). Mitigation strategies, including careful question design and sampling, helped mitigate these challenges to yield reliable, generalisable results.

3.4 Data collection methods

Data for this study was collected using online structured questionnaires, selected for their efficiency in gathering quantitative data from many respondents (Taherdoost, 2022). Online surveys are particularly effective for studies involving dispersed populations, as they enable researchers to reach respondents across various geographic locations quickly and cost-effectively (Evans and Mathur, 2018). This method aligns with previous research in South Africa, such as the study by Maduku et al. (2016), which examined the adoption of mobile banking among consumers using structured questionnaires. The study demonstrated the effectiveness of online surveys in collecting data on technology adoption, particularly in sectors with diverse and geographically distributed respondents.

The questionnaires used in this study were carefully designed to collect data on technological, organisational and environmental factors influencing the adoption of AI for PPM. Structured questionnaires ensure consistency, as all respondents answer the same questions in a standardised format, improving the reliability and validity of the data (Bhattacherjee, 2012). Additionally, electronic distribution allowed the study to achieve a broad reach, enhancing the generalisability of the findings specific to the financial services sector. To maximise response rates and minimise non-response bias, the survey design incorporated strategies such as clear instructions, concise questions and follow-up reminders. These measures are consistent with best practices for online surveys, as Creswell (2014) highlighted, ensuring high-quality data collection and efficiency.

3.5 Population and sample

Population

This study focused on employees from South African financial services organisations, selected for their direct involvement in operations and strategic initiatives, providing valuable insights into AI adoption for PPM. The sector's vital role in the economy and growing reliance on AI underscore the relevance of this population. Research such as Nel and Boshoff (2021) highlights the importance of employees across various roles in facilitating technology adoption within organisations. Similarly, Makanyeza and Mutambayashata (2018) demonstrate the critical role employees play in adopting innovative technologies, reinforcing the suitability of targeting this population. Focusing on employees across South Africa's financial services sector ensures the findings reflect diverse perspectives and experiences, enhancing the study's generalisability in this sector. This approach offers valuable insights into the key factors that drive or hinder AI adoption, providing actionable recommendations for both practitioners and policymakers.

Sample and sampling method

A representative sample of employees in financial services organisations in South Africa was drawn to explore the factors influencing the adoption of AI for PPM. Using Cochran's (1977) formula for sample size determination as illustrated in Figure 6, a required sample size (n_0) of 376 participants was calculated. This calculation assumed a response distribution (p) of 50%, a confidence level (Z) of 95% and a margin of error (e) of 5%, ensuring a statistically robust representation of the population.

$$n_0 = \frac{Z^2 \cdot p \cdot (1 - p)}{e^2}$$

Figure 6. Cochran's sample size formula

This approach has been widely applied in social science research to ensure an appropriate sample size for large populations (Lohr, 2009). Key respondents included IT executives, IT specialists and project managers. These roles were identified as critical to understanding the organisational and technological dynamics of AI implementation. This focus was informed by studies such as Nel and Boshoff (2021), which investigated technology adoption in financial institutions.

The study employed purposive non-probability sampling and snowball sampling to select participants. This approach was effective in targeting individuals with specific expertise and knowledge relevant to the research objectives (Bhattacherjee, 2012). Purposive sampling ensured the inclusion of respondents most likely to provide valuable insights, while snowball sampling helped identify additional participants through referrals, thereby expanding the reach of the study (Creswell, 2014). This method had been successfully applied in similar research, such as Tyson and Sauers (2021), which examined Artificial intelligence adoption in K-12 education, demonstrating its applicability to technology adoption studies. Although non-probability sampling restricted the generalisability of the findings, it was appropriate for targeting the study's specialised population. By combining purposive and snowball sampling, the study ensured the inclusion of participants with the most relevant expertise while increasing the sample size through network-based recruitment.

Academic fit and methodological literature

The chosen research approach, design, data collection methods and sampling strategy were well-aligned with the principles outlined in the methodology literature (Bell et al., 2019; Bhattacherjee, 2012). The positivist paradigm ensured objectivity and empirical thoroughness, while the cross-sectional design provided a comprehensive view of current trends and relationships. The use of structured questionnaires facilitated efficient and reliable data collection, and purposive sampling ensured a representative and generalisable sample (Bell et al., 2019).

Adhering to these established methodologies aims to contribute robust and credible findings to AI adoption for PPM within financial services. The alignment with methodological best practices enhanced the validity and reliability of the research, ensuring that the results are both scientifically sound and relevant.

3.6 The research instrument

The research instrument (Appendix B: Research Instrument) chosen for this study was an online structured questionnaire designed to systematically collect data from employees in financial service organisations in South Africa regarding the adoption of AI for PPM. This instrument was crafted to address the four core research questions and was aligned with the TOE framework, ensuring a comprehensive examination of the technological, organisational and environmental factors influencing AI adoption (Bell et al., 2019). Demographic data was collected to identify patterns in AI adoption perceptions based on respondent characteristics. Section A included age, gender, education level, job role, years of experience, and exposure to AI technologies to assess their potential influence on adoption readiness. These insights help contextualise the findings and inform tailored strategies for effective AI implementation in diverse organisational settings. A 5-point Likert scale was used to evaluate the items, with responses ranging from 1 (strongly disagree) to 5 (strongly agree). The structured questionnaire was particularly suitable for this research as it allowed for the efficient collection of standardised data, which is essential for analysing the dependent variable of AI adoption.

The online questionnaire was divided into five sections, each tailored to gather specific data relevant to the study's objectives:

a. Demographic data
b. Technological factors
c. Organisational factors
d. Environmental factors
e. Adoption of TOE constructs combined for PPM

The questionnaire was aligned with the research questions and the TOE framework to attempt a holistic understanding of the factors affecting AI adoption for PPM. Each part of the questionnaire addressed specific technological, organisational and environmental elements outlined in the conceptual TOE framework. This alignment ensured that the data collected was relevant and comprehensive, allowing for a thorough analysis of the factors influencing AI adoption.

3.7 Measurement Items

Table 2. Measurement items

Constructs	Measurement Item	Source
Technological		
Availability of AI Technologies (AAT)	**(AAT1)** My organisation has sufficient access to state-of-the-art AI technologies. **(AAT2)** The necessary AI software is easily obtainable in my organisation. **(AAT3)** My organisation can easily acquire the AI technologies needed.	(Gupta et al., 2022; Kumari et al., 2024; Srinivasan et al., 2024)
Technological Infrastructure (TIN)	**(TIN1)** The technology infrastructure of my business unit can support AI-related technology. **(TIN2)** The development of AI technology is compatible with my organisation's legacy systems. **(TIN3)** My organisation's current IT systems can scale to support AI.	(Costa et al., 2022; Gupta et al., 2022; Mohammad et al., 2022)
Data Quality (DAQ)	**(DAQ1)** My organisation's data sources for AI applications are reliable. **(DAQ2)** The data available for AI in my organisation is accurate. **(DAQ3)** The data my organisation uses for AI is consistent across different sources.	(Al-Khatib, 2023; Costa et al., 2022; Salah and Ayyash, 2024)
Organisational		
Top Management Support (TMS)	**(TMS1)** My top management encourages innovation through AI. **(TMS2)** My top management allocates the necessary resources for AI adoption. **(TMS3)** My organisation's top management is involved in strategic planning for AI adoption.	(Al-Khatib, 2023; Nguyen et al., 2022; Costa et al., 2022)
Skilled AI Technical Resources (STR)	**(STR1)** My organisation has skilled technical staff for AI implementation. **(STR2)** My organisation provides adequate training for staff working on AI technologies. **(STR3)** My organisation can effectively recruit skilled AI professionals.	(Aniceski et al., 2024; Kumari et al., 2024; Schoeman et al., 2021)
Organisational Culture (OGC)	**(OGC1)** My organisation encourages innovation and experimentation with AI technologies.	(An et al., 2024;

Constructs	Measurement Item	Source
	OGC2: Employees in my organisation are open to adopting new AI tools and technologies. **(OGC3)** Collaboration and knowledge sharing about AI are encouraged in my organisation.	Schoeman and Seymour, 2022; Salah and Ayyash, 2024)
Environmental		
Government Regulation (GOR)	**(GOR1)** South African government regulations support the adoption of AI. **(GOR2)** My organisation collaborates with regulatory bodies to ensure AI compliance. **(GOR3)** My organisation actively monitors changes in government regulations related to AI.	(Hanna et al., 2020; Oliver Wyman, 2024; Wang et al., 2024)
Market Competition (MAC)	**(MAC1)** My organisation's AI strategies are shaped by competitive pressures. **(MAC2)** Competitors' use of AI drives my organisation to adopt similar technologies. **(MAC3)** My organisation invests in AI to respond to market competition.	(Badghish and Soomro, 2024; Salah and Ayyash, 2024)
Investment Conditions (INV)	**(INV1)** My organisation benefits from a stable economic environment for AI investments. **(INV2)** My organisation has the financial resources needed for significant AI investments. **(INV3)** Supportive financial policies encourage my organisation to invest in AI.	(Abdurrahman et al., 2024; Al-Khatib, 2023; Dewi and Wiksuana, 2023; Mohammad et al., 2022)
Adoption for PPM		
TOE Combined Effect (CEF)	**(CEF1)** The interaction of technological, organisational and environmental factors supports AI adoption for PPM in my organisation. **(CEF2)** Combining technological, organisational and environmental factors improves resource allocation for PPM in my organisation. **(CEF3)** Combining technological, organisational and environmental factors improves efficiency and productivity for PPM in my organisation.	(Baker, 2012; Gaffley, 2021)

3.8 Pilot testing

A pilot test was conducted to ensure the survey questions were clear, easy to understand and unbiased (Nardi, 2018), while confirming the validity and reliability of the TOE framework. Pilot testing is a crucial step in research, as it allows researchers to identify and rectify potential issues with the survey instrument, refine its structure and enhance its overall effectiveness. This step helps reduce measurement errors and ensures the survey accurately captures the intended constructs, thereby leading to more robust and credible findings (Bell et al., 2019; Bhattacherjee, 2012). Pilot tests typically involve a small group from the target population to provide actionable feedback that improves the main study (Oates, 2006).

The pilot test for this study included five respondents whose roles represented a diverse subset of the target population: an Automation Specialist, Solutions Architect, Business Analyst, Programme Manager and Senior Project Manager. These respondents were spread across Banking (2), Insurance (2) and Financial services - Other (1). This spread ensured that the feedback captured a range of perspectives relevant to the study's objectives. A small pilot group was chosen deliberately to balance the need for constructive feedback with the preservation of responses for the main study, as a larger pilot group would have reduced the available sample for the final survey (Van Teijlingen and Hundley, 2001). Four respondents added comments at the end of the survey. Based on the responses, the survey instrument was revised to enhance clarity, relevance and usability before distribution to the full sample.

Respondents were asked the following feedback questions after completing the pilot survey:

a. Were the questions easy to understand? If any were unclear, please specify which ones.
b. Was the length of the survey appropriate? Please specify whether it felt too long or too short and how much time it took you to complete.
c. Do you think any important questions were missing? If so, please list them.

Pilot feedback

Feedback on the pilot survey in Appendix C: Pilot Feedback provided useful insights to improve the clarity, structure and content of the questionnaire. Respondents generally found the questions easy to understand, although some noted areas that needed clarification. The questions on factors affecting resource allocation, efficiency and productivity were felt to be vague, and it was suggested that these factors could be specified or examples given. Guidance was also recommended on how to indicate years of experience, for example in relation to rounding conventions. The length of the survey was considered appropriate, with an average completion time of five minutes. Suggestions for improvement included the addition of a progress indicator. In terms of content, respondents recommended adding a brief definition of AI technologies at the beginning to ensure a standardised understanding. They also suggested adding an "I do not know" option on the Likert scale for respondents with limited knowledge. These insights fed into the refinements to improve clarity, relevance and engagement.

The feedback was carefully analysed to identify inconsistencies and ensure respondents interpreted the survey items uniformly. All the pilot test responses were excluded from the final data set but were instrumental in improving the design and structure of the survey instrument (Appendix B: Research Instrument).

Survey changes

Following the pilot survey feedback, several refinements listed in Appendix D: Summary of Pilot Survey Changes were made to enhance clarity, completeness, and the overall respondent experience. A progress bar was introduced on each page to improve navigation and provide a clear indication of survey completion. To capture respondents' job levels more effectively, a new question was added with four structured response options: Top Level Management, Middle Level Management, First Line Management, and Specialist or Non-Managerial. The question on organisational type was expanded to include an additional option, "None of the above," to ensure broader applicability. The item on AI technologies was refined by specifying key examples, including Machine Learning, Deep Learning, and Generative AI, to provide greater contextual clarity. The reference to TOE factors was revised to improve comprehension by expanding the acronym to Technology, Organisational, and Environmental, and incorporating a clarification that these factors had been discussed in the preceding questions. These modifications strengthened the survey's precision, structure, and usability.

3.9 Procedure for data collection

The procedure for data collection in this study involved a process designed to ensure efficient, systematic and reliable data collection from a representative sample of employees from financial service organisations in South Africa. The steps outlined below provide detailed guidance for replicating the study:

Table 3. Procedure for data collection

Step	Task	Description
Step 1	Preparation of the questionnaire	The online structured questionnaire was prepared and finalised, ensuring all questions were clear, concise and aligned with the research objectives. It was divided into five sections: Demographic data, Technological factors, Organisational factors, Environmental factors and Adoption. These sections were designed to comprehensively address all TOE constructs relevant to PPM, with each section focusing on specific aspects of the research questions.
Step 2	Identifying the sample	A list of potential respondents was compiled from various sources, including industry directories, professional associations, online databases of employees in South Africa's financial services organisations and the researcher's network of contacts. The target was to secure a minimum of 120 responses to ensure sufficient data for robust statistical analysis.

Step	Task	Description
Step 3	Distribution of the questionnaire	The questionnaire was distributed to the identified respondents via email and WhatsApp. Each message included a personalised cover letter explaining consent, the purpose of the research, the importance of their participation and assurances regarding the confidentiality and anonymity of their responses. The participant information sheet provided clear instructions on completing and returning the questionnaire.
Step 4	Follow-up	To maximise response rates, follow-up emails and WhatsApp messages were sent to all respondents at the end of week 1 and week 4 after the initial distribution. These follow-ups served as reminders, reiterating the study's importance and the value of their participation.
Step 5	Data collection period	The data collection period lasted approximately 8 weeks. This duration provided sufficient time for respondents to complete the questionnaire while ensuring the data was collected promptly for analysis.
Step 6	Data management	Upon receipt, responses were securely stored on the Qualtrics platform, where each response was assigned a unique identifier. The data was checked for completeness and consistency and any discrepancies were addressed as necessary.

The questionnaire was distributed via email and WhatsApp because of their efficiency, cost-effectiveness and ability to reach dispersed respondents quickly. These methods allowed respondents to complete the survey conveniently, boosting response rates while ensuring anonymity and confidentiality for honest responses. The structured format maintained standardisation, enhancing data reliability and validity (Bhattacherjee, 2012; Van Selm and Jankowski, 2006). Similar methods were used by Chukwuere et al. (2017) to gather survey data efficiently in academic research.

3.10 Data analysis and interpretation

The data collected through the Qualtrics platform was exported into SPSS to create and prepare the data file for analysis. This process included coding variables, checking for missing data and ensuring the dataset was ready for statistical analysis. The prepared data file facilitated a systematic approach to analysis, enabling the use of appropriate statistical techniques.

The data analysis combined descriptive statistics, regression analysis and Structural Equation Modelling (SEM) to ensure a comprehensive approach. Covariance-Based Structural Equation Modelling (CB-SEM) was selected over Partial Least Squares Structural Equation Modelling (PLS-SEM) due to its suitability for testing and confirming theories, as it assesses overall model fit (Hair et al., 2021). CB-SEM was also preferred for its ability to handle reflective models, where constructs influence observed variables and because the study's sample size was sufficient for reliable results. SEM was particularly appropriate as it is widely used in adoption studies employing the TOE framework for analysing complex relationships between variables. For example, Gupta et al. (2022) used SEM to study AI adoption in the insurance industry, showing its value for examining TOE dimensions. Their conceptual model is like the one for this study. Min and Kim (2024) applied SEM to explore how productivity and service stability affect AI adoption in IT networks. Al-Khatib (2023) similarly used SEM to investigate how TOE factors influence generative AI adoption and its impact on innovation. These studies show that SEM is highly suitable for research on technology adoption. This approach provided a strong basis for addressing the research questions and analysing the factors that affect AI adoption for PPM in South African financial services. The steps taken are outlined below.

Descriptive statistics extracted from SPSS to summarise and describe the key features of the collected data. The mean, median, mode, standard deviation and frequency distributions were calculated to understand the sample's demographic characteristics. These statistics offered insights into respondents' organisational positions, years of experience and organisational types, forming the foundation for further analysis.

Regression analysis was conducted through AMOS to evaluate the relationships between the independent variables (technological, organisational and environmental factors) and the dependent variable, the adoption of AI for PPM. Multiple regression analysis identified significant predictors, with regression coefficients and significance levels revealing the strength and direction of these relationships. This step ensures the identification of key factors influencing AI adoption (Oates, 2006).

SEM was applied in AMOS to validate the conceptual model and test hypothesised relationships among variables. SEM, which integrates factor analysis and regression analysis, was suitable for examining relationships between observed and latent variables within the theoretical framework. The following steps were undertaken:

1. The model specification defined hypothesised relationships among variables based on the TOE framework.
2. The model identification process ensured that the model met the necessary conditions for estimation.
3. Model estimation was performed using AMOS software, with parameters estimated and model fit assessed using indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) and Chi-square.
4. The model evaluation involved reviewing the fit indices and making refinements where necessary to improve the model.
5. Model interpretation was conducted by analysing the standardised path coefficients to determine the significance and strength of relationships among variables (Kline, 2016; Byrne, 2016).

Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were conducted in AMOS to assess underlying relationships among variables and validate the measurement model. EFA identified latent factors influencing AI adoption, while CFA confirmed the factor structure. Reliability and validity were evaluated using Cronbach’s alpha and Composite Reliability (CR) for internal consistency and Average Variance Extracted (AVE) for convergent validity (Hair et al., 2019).

The selected methods aligned with the study’s positivist paradigm and cross-sectional design. The integration of SEM with descriptive and regression analyses enabled a rigorous examination of the factors influencing AI adoption for PPM. This multi-method approach ensured that findings were reliable and relevant, providing meaningful insights into AI adoption in the South African financial services sector (Bell et al., 2019; Byrne, 2016; Collier, 2020).

3.11 Ethical considerations

This study was approved by the Wits Business School Ethics Committee (protocol number WBS/DB2447481/221), with the ethics clearance certificate provided in Appendix E: Ethics Clearance Certificate. The research adhered to strict ethical principles, including voluntary participation, informed consent, anonymity and confidentiality. A cover letter detailing the study's objectives and ethical assurances was provided to respondents and is included in Appendix A: Participant Information Sheet.

Participants were informed that participation was voluntary, with no penalties for non-participation and they could withdraw their data at any time without consequences. The cover letter assured anonymity, stating that responses would not be linked to individuals or their business units.

To ensure confidentiality, no sensitive client or organisational data was collected, safeguarding sensitive data. All collected data was securely stored, accessible only to the researcher and not shared with third-party organisations or other surveyed business units. Analysis was conducted in aggregate form, ensuring individual responses remained unidentifiable. These measures upheld respondents’ rights and ensured the integrity and professionalism of the research process (Oates, 2006).

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

This chapter presents the findings from the data collected through the study's survey questionnaire, which addresses the four research questions and tests the hypotheses underpinning the study on adopting AI for PPM in South African financial services. The chapter adopts a structured approach aligned with the SEM methodology. It begins with discussing the data screening process, including handling missing data and ensuring the dataset's suitability for analysis. This is followed by an overview of the survey respondents' demographic and professional profiles. Next, descriptive statistics for all variables in the measurement model are summarised, leading to an evaluation of the constructs' reliability and validity through Confirmatory Factor Analysis (CFA). The chapter concludes with hypothesis testing using the structural model, identifying the most significant factors influencing AI adoption for PPM.

4.2 Data screening

The dataset comprised 150 survey responses from a sample of 376 (39.89%). Of these, 10 responses were excluded as they were from employees working in non-financial services organisations, which fell outside the scope of the study. The screening was conducted using Question 7, which presented respondents with a dropdown menu asking, "Which of the following best describes your organisation?" Respondents who selected "None of the above" were screened out. Additionally, 22 responses were incomplete and were therefore excluded from the analysis. After addressing these exclusions, the final dataset comprised 118 valid responses representing IT and project management employees within the financial services sector. The response rate aligns with that of other studies using the TOE framework, such as The Application of Technology Organisation Environment Framework in the Approaches for Smart Warehouse Adoption by Khalid et al. (2024) where the response rate achieved was 35.38% and the Adoption of a technology–organisation–environment framework in the digitisation decision of inventory management by Zulkipli et al. (2024), with a response rate of 32.14% achieved. These studies justify these rates as typical for technical and executive stakeholders research. This is especially relevant for AI adoption studies where respondents are decision-makers with limited availability.

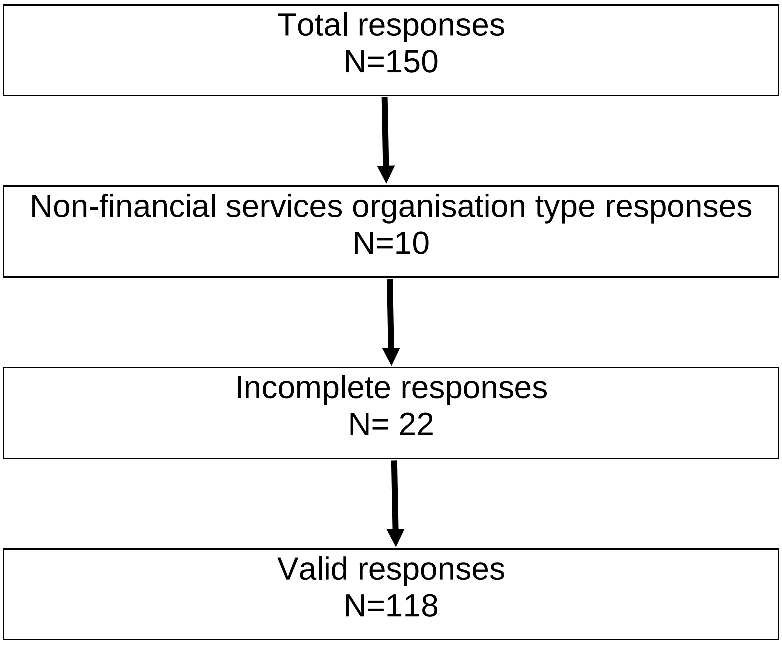

Figure 7. Data screening

4.2.1 Missing data

The decision to exclude 22 responses with more than 10% missing items was based on the need to ensure data integrity and reliability in the analysis. Responses with important missing data can introduce bias, reduce statistical power and compromise the validity of the findings (Hair and Sarstedt, 2019). By setting a 10% missing data threshold, the study aimed to retain sufficiently complete responses to provide meaningful insights while maintaining consistency and robustness in the dataset. The remaining responses were completed in full. This approach aligns with best practices in data handling, where incomplete responses beyond a reasonable threshold are excluded to minimise potential inaccuracies in the results (Hair and Sarstedt, 2019).

4.2.2 Reverse coding

Reverse coding is a widely recognised technique used in survey research to address questions phrased in the opposite direction of the measured construct. This method is employed to mitigate response bias, such as acquiescence or socially desirable responding, by encouraging respondents to carefully consider their answers rather than responding in a habitual or inattentive manner (Podsakoff et al., 2003). However, in this study, all questionnaire items were consistently aligned with the measured constructs, eliminating the need for reverse coding. This approach ensured clarity and minimised the potential for confusion arising from negatively worded or reverse-scored items.

4.2.3 Outlier detection

Outlier detection was not conducted in this study due to the nature of the research and the underlying dataset. Outliers can significantly impact statistical analyses, particularly when they arise from data collection or entry errors. However, in cases where outliers reflect genuine responses within the population of interest, their removal can distort the analysis and reduce the generalisability of findings (Aguinis et al., 2013). Given that the dataset in this study was derived from a well-defined and targeted population of IT and project management employees within the South African financial services sector, all responses were deemed relevant and reflective of the population. Furthermore, the data screening process, including validity checks, ensured that no extreme or erroneous values compromised the dataset's integrity, thus justifying the decision not to perform additional outlier detection.

4.3 Response profile

The section below provides a summary of the demographics of the survey respondents. The seven factors presented include age group, education level, job title, job level, role in IT decision making, current tenure and organisation type. The demographic statistics were obtained using SPSS. The dataset was imported into SPSS and the relevant demographic variables were selected for analysis. The output provided the frequencies and percentages for each demographic item, which were then reviewed to ensure the accuracy and completeness of the demographic profile for the study.

The section below summarises the demographic profile of the 118 valid responses collected from executive, IT and project management employees in the South African financial services sector.

4.3.1 Age distribution of respondents

The age distribution of respondents showed that the largest group was aged 31–40 (n = 52; 44.1%), followed by those aged 41–50 (n = 47; 39.8%). Smaller proportions were aged 21–30 years (n = 9; 7.6%), 51–60 years (n = 7; 5.9%) and over 60 years (n = 3; 2.5%). This age distribution suggests that most respondents were mid-career employees aged 31 to 50, who may be the most engaged or influential in AI adoption due to their career experience and decision-making roles.

Table 4. Age distribution summary

Age (years old)	Frequency	Percentage
21-30	9	7,6
31-40	52	44,1
41-50	47	39,8
51-60	7	5,9
>60	3	2,5

4.3.2 Education level of respondents

The education level of respondents showed that most held a postgraduate qualification (n = 62; 52.5%). Equal proportions had either a diploma (n = 24; 20.3%) or a bachelor's degree (n = 24; 20.3%). Smaller groups included those with other qualifications (n = 7; 5.9%) and high school education (n = 1; 0.8%). This reflects a highly educated participant group, which may suggest that the study's findings are shaped by individuals with advanced knowledge and expertise, potentially influencing their perspectives on AI adoption.

Table 5. Education level summary

Education level	Frequency	Percentage
High school	1	0,8
Diploma	24	20,3
Bachelor	24	20,3
Post-graduate	62	52,5
Other	7	5,9

4.3.3 Job title of respondents

The largest group was Project Managers (n = 19; 16.1%), followed by IT Specialists and Managers (n = 8; 6.8%) and Senior Project Managers, Development Managers and Test Analysts (n = 7; 5.9%), suggesting that the study captures insights from individuals likely to have direct involvement or influence in AI adoption decisions for PPM. Smaller groups included Delivery Managers, IT Directors and Architects (n = 5; 4.2%) and Technical Leads, CIOs and Software Engineers (n = 4; 3.4%). Other roles, such as Product Managers, System Analysts and Senior Managers, accounted for less than 3% each, highlighting a diverse range of professional roles.

Table 6. Job title summary

Job title	Frequency	Percentage
Architect	5	4.2
Business Analyst	2	1.7
Chief Financial Officer	1	0.8
Chief Information Officer	4	3.4
Chief Technology Officer	1	0.8
Data Analyst	1	0.8
Data Modeler	2	1.7
Delivery Manager	5	4.2
Development Manager	7	5.9
Finance Manager	1	0.8
Financial Analyst	1	0.8
Head of Project Office	2	1.7

Head of Quality Assurance	2	1.7
IT Consultant	2	1.7
IT Director	5	4.2
IT Finance Manager	1	0.8
IT Financial Analyst	2	1.7
IT Specialist	8	6.8
Manager	8	6.8
Managing Director	1	0.8
Product Manager	3	2.5
Programme Manager	2	1.7
Project Manager	19	16.1
Senior Business Analyst	3	2.5
Senior Development Manager	2	1.7
Senior Manager	3	2.5
Senior Project Manager	7	5.9
Software Engineer	4	3.4
System Analyst	3	2.5
Technical Lead	4	3.4
Test Analyst	7	5.9

4.3.4 Job level of respondents

The job level distribution of respondents showed that the largest group consisted of specialists and non-managerial roles (n = 42; 35.6%), followed by middle-level management (n = 38; 32.2%). Top-level management accounted for a smaller proportion (n = 24; 20.3%), while first-line management represented the smallest group (n = 14; 11.9%). This distribution highlights a balanced representation of managerial and specialist roles, indicating that the study captures insights from decision-makers and those with specialised expertise relevant to AI adoption.

Table 7. Job level summary

Job level	Frequency	Percentage
Top-Level Management	24	20,3
Middle-Level Management	38	32,2
First-Line Management	14	11,9
Specialist/Non-managerial	42	35,6

4.3.5 Role tenure of respondents

The respondents' current role tenure distribution revealed that the largest group had been in their roles for 2–4 years (n = 41; 34.7%), followed by those with over 10 years of tenure (n = 27; 22.9%). Respondents with 5–7 years in their roles accounted for 20.3% (n = 24), while smaller proportions had 0–1 year (n = 17; 14.4%) or 8–10 years (n = 9; 7.6%) of tenure. This indicates a balanced mix of early, mid and long-tenured employees among the respondents, suggesting a range of perspectives, from fresh insights to experienced viewpoints.

Table 8. Current role tenure distribution summary

Current role tenure (years)	Frequency	Percentage
0-1	17	14,4
2-4	41	34,7
5-7	24	20,3
8-10	9	7,6
>10	27	22,9

4.3.6 IT decision making role of respondents

The distribution of respondents based on their role in IT decision making showed that the majority were involved in IT decision making (n = 81; 68.6%), while a smaller proportion were not (n = 37; 31.4%). This indicates a strong representation of decision-makers, which is crucial for this AI adoption study. Their roles in evaluating, approving and implementing AI ensure the study captures insights from those directly influencing adoption, enhancing the validity and relevance of the findings for adopting AI for PPM.

Table 9. IT decision-making role summary

IT decision-making role	Frequency	Percentage
No	37	31,4
Yes	81	68,6

4.3.7 Organisation type of respondents

The organisation type distribution of respondents indicated that the most prominent groups were from the insurance sector (n = 41; 34.7%) and banking sector (n = 37; 31.4%). Respondents from other financial services accounted for 24.6% (n = 29), while smaller proportions were from advisory (n = 5; 4.2%), wealth management (n = 4; 3.4%) and mutual funds (n = 2; 1.7%). This reflects a strong representation of employees from core financial services organisations, providing focused insights into AI adoption practices relevant to this study.

Table 10. Organisation type

Organisation type	Frequency	Percentage
Banking	37	31,4
Insurance	41	34,7
Advisory	5	4,2
Wealth management	4	3,4
Mutual funds	2	1,7
Financial Services – Other *	29	24,6

* The “Other" classification of financial services includes organisations operating in non-mainstream segments of the financial services sector, such as credit bureaus, brokers and payment processors.

4.3.8 Summary of demographic data analysis

The demographic analysis highlighted key trends among respondents. Most (31–50 years) were mid-career employees with substantial experience. Job titles emphasised project management roles critical for AI adoption for PPM, while job levels showed a balanced mix, with specialists as the largest group. Tenure was concentrated in 2–4 years and over 10 years, reflecting diverse experience levels. The majority held IT decision-making roles, ensuring informed perspectives. Organisation types were dominated by insurance and banking, with contributions from advisory, wealth management and other financial services, showcasing industry diversity and enhancing the study's credibility.

4.4 Descriptive statistics and normality

The descriptive statistics section provides an overview of the data characteristics used in the SEM process. It examines the means, standard deviations, skewness and kurtosis of the observed variables to assess their distributions and suitability for analysis. This step ensures that the data meet SEM assumptions, such as normality and variability while offering initial insights into respondents' perceptions across the study constructs. Acceptable thresholds for skewness typically range from -1 to +1, indicating a distribution close to normal. For instance, Hair et al. (2019) suggest that data is considered normal if skewness is between -2 to +2 and kurtosis is between -7 to +7. Similarly, George and Mallery (2003) as well as Kline (2016) consider skewness and kurtosis values between -2 and +2 as acceptable for proving normal univariate distribution. The descriptive statistics were obtained using SPSS, where the relevant variables were selected for analysis. The output was reviewed to confirm the suitability of the data for further SEM analysis.

4.4.1 Descriptive statistics for technology factors

The overall descriptive statistics for the technology context, consisting of the three latent constructs Availability of AI Technologies (AAT), Technological Infrastructure (TIN) and Data Quality (DAQ), suggested moderate to moderately high perceptions of these constructs. The mean scores ranged from 3.10 (TIN2) to 3.94 (AAT3), with all constructs showing variability in responses, as indicated by standard deviations ranging from 0.876 to 1.078. For skewness, the values fell within acceptable limits (-1 to +1), with AAT3 and TIN1 showing slight left skew, indicating a tendency for higher agreement among respondents. The skewness for TIN2 was near zero, reflecting a more balanced distribution. Similarly, the kurtosis values (-1.158 to 0.848) indicated that the data distributions were close to normal, with TIN1 showing a slight peak and TIN2 with a flatter distribution. In summary, the descriptive statistics suggested that the data for all three constructs were appropriate for further analysis, with no major deviations from normality and sufficient variability to explore the relationships between these constructs in the SEM process.

Table 11. Technology factors central tendency

Latent Construct	Items	Mean	SD	Skewness	Kurtosis
Availability of AI Technologies	AAT1	3,58	1,041	-0,461	-0,489
	AAT2	3,39	1,078	-0,042	-1,158
	AAT3	3,94	0,963	-0,813	0,085
Technological Infrastructure	TIN1	3,86	0,876	-0,971	0,848
	TIN2	3,10	1,065	0,226	-0,613
	TIN3	3,75	0,997	-0,888	0,517
Data Quality	DAQ1	3,69	1,000	-0,865	0,592
	DAQ2	3,66	0,972	-0,920	0,785
	DAQ3	3,37	1,011	-0,403	-0,518

4.4.2 Descriptive statistics for organisational factors

The descriptive statistics for the organisational factors, including Top Management Support (TMS), Skilled AI Technical Resources (STR) and Organisational Culture (OGC), indicated positive perceptions among respondents. Mean scores ranged from 3.29 (STR2) to 4.00 (TMS1), reflecting moderately high levels of agreement across items. Standard deviations varied between 0.824 and 1.110, suggesting moderate variability in responses. Skewness values for all items fell within acceptable ranges, from -1.038 (OGC1) to -0.142 (STR2), indicating a tendency toward agreement, particularly for items within OGC. Kurtosis values ranged from -0.894 (STR2) to 1.177 (OGC3). Items related to OGC exhibited slightly leptokurtic distributions, suggesting a clustering of responses around central values, while TMS and STR displayed distributions closer to normal, with kurtosis values near zero. Leptokurtic distributions are variable distributions with wide tails and have positive kurtosis. Overall, these descriptive statistics suggested that respondents perceived a moderate to high level of support for top management, the availability of skilled AI technical resources and a strong organisational culture. The distributions showed no significant deviations from normality, confirming the data's suitability for further analysis.

Table 12. Organisational factors central tendency

Latent Construct	Items	Mean	SD	Skewness	Kurtosis
Top Management Support	TMS1	4,00	0,961	-0,823	-0,164
	TMS2	3,33	1,110	-0,421	-0,703
	TMS3	3,77	0,991	-0,865	0,584
Skilled AI Technical Resources	STR1	3,43	1,098	-0,534	-0,565
	STR2	3,29	1,079	-0,142	-0,894
Organisational Culture	OGC1	3,91	0,915	-1,038	1,075
	OGC2	3,83	0,860	-0,811	1,038
	OGC3	3,93	0,824	-0,898	1,177

4.4.3 Descriptive statistics for environmental factors

The descriptive statistics for the environmental factors, including Government Regulation (GOR), Market Competition (MAC) and Investment Conditions (INV), indicated moderate perceptions among respondents. Mean scores ranged from 3.06 (GOR1) to 3.82 (INV2), reflecting moderate agreement across the items, with standard deviations varying from 0.913 to 1.079, suggesting some variability in responses. Skewness values for all items fell within acceptable ranges, from -0.807 (INV2) to -0.120 (GOR1), indicating a tendency toward higher agreement, particularly for INV2. The kurtosis values ranged from -0.734 to 0.163, with GOR items displaying near-normal distributions, while MAC and INV items exhibited slightly platykurtic distributions, suggesting an even spread of responses. Overall, these descriptive statistics suggested that respondents perceived government regulation, market competition and investment conditions as moderate to high factors influencing their views, with no significant deviations from normality, making the data suitable for further analysis.

Table 13. Environmental factors central tendency

Latent Construct	Items	Mean	SD	Skewness	Kurtosis
Government Regulation	GOR2	3,47	0,940	-0,497	0,163
	GOR3	3,42	1,016	-0,485	-0,047
Market Competition	MAC1	3,56	0,974	-0,367	-0,411
	MAC2	3,50	1,027	-0,313	-0,734
	MAC3	3,40	1,079	-0,355	-0,638
Investment Conditions	INV1	3,48	0,949	-0,255	-0,383
	INV2	3,82	0,993	-0,807	0,336
	INV3	3,53	0,913	-0,420	0,201

4.4.4 Descriptive statistics for combined TOE factors

The descriptive statistics for the combined Adoption effect (CEF) indicated positive perceptions among respondents. Mean scores ranged from 3.60 (CEF2) to 3.88 (CEF3), reflecting moderately high agreement across the items, with standard deviations varying from 0.764 to 0.907, suggesting some variability in responses. Skewness values for all items fell within acceptable ranges, from -0.880 (CEF3) to -0.518 (CEF2), indicating a tendency toward higher agreement, particularly for CEF3. The kurtosis values ranged from 0.077 to 1.199, with CEF1 exhibiting a slightly leptokurtic distribution, suggesting a clustering of responses around certain values, while CEF2 and CEF3 displayed distributions closer to normal. Overall, these descriptive statistics suggested that respondents perceived a moderate to high level of influence from the combined TOE factors on AI adoption, with no significant deviations from normality, confirming the data's suitability for further analysis.

Table 14. Descriptive statistics for adoption effect on PPM

Latent Construct	Items	Mean	SD	Skewness	Kurtosis
Adoption TOE Effect	CEF1	3,75	0,764	-0,816	1,199
	CEF2	3,60	0,907	-0,518	0,077
	CEF3	3,88	0,888	-0,880	0,973

4.4.5 Normality testing: Skewness and Kurtosis

The assumption of normality was assessed by examining the skewness and kurtosis of the indicators before conducting the measurement model analysis. The results presented in Table 15 indicate that these criteria were satisfied, thereby confirming that the normality assumption was upheld.

Table 15. Normality testing

Variable	Description	Skewness	Kurtosis
AAT	Availability of AI Technologies	-0.439	-0.520
TIN	Technological Infrastructure	-0.545	0.251
DAQ	Data Quality	-0.730	0.287
TMS	Top Management Support	-0.703	-0.094
STR	Skilled AI Technical Resources	-0.338	-0.730
OGC	Organisational Culture	-0.916	1.097
GOR	Government Regulation	-0.491	0.058
MAC	Market Competition	-0.345	-0.594
INV	Investment Conditions	-0.494	0.051
CEF	TOE Combined Effect	-0.738	0.750

4.4.6 Common Method Bias

Common Method Bias (CMB) refers to the artificial inflation of relationships between independent and dependent variables caused by using the same measurement method for both (Hair and Sarstedt, 2019). To assess the presence of CMB, Harman’s single-factor test was employed, wherein all scale items were subjected to an exploratory factor analysis. In this study, Principal Component Analysis (PCA) was conducted using SPSS. The analysis revealed that a single factor accounted for 33.765% of the variance, as shown in the table. This value is well below the commonly accepted threshold of 50%, as described by Podsakoff et al. (2003), indicating that no single factor dominates the data. Consequently, it was concluded that CMB is not a significant concern in this study, thereby validating the dataset and supporting the continuation of structural analyses.

Table 16. CMB Analysis

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.129	33.765	33.765	10.129	33.765	33.765

4.5 Measurement model analysis (CFA)

The measurement model defines the relationships between variables and their associated indicators as described by Hair et al. (2019) and employs Confirmatory Factor Analysis (CFA) to evaluate key aspects such as reliability, convergent validity and discriminant validity (Hair and Sarstedt, 2019). CFA is an essential tool for testing theoretical models, as it assesses how well the observed variables represent underlying latent constructs. Developed further by Hair et al. (2019), CFA provides a robust analytical framework to test conceptually grounded theories and determine how measured indicators reflect significant variables. By integrating CFA results with validity assessments, researchers can evaluate the quality and robustness of their theoretical measurement (Hair et al., 2019, 2021). This process is fundamental to ensuring that valid conclusions are drawn from valid measurements, establishing CFA as a pivotal element in research design and analysis.

4.5.1 Measurement model fit assessment

In this study, CFA was conducted to evaluate the measurement model designed in AMOS. Following model specification, the fit of the latent variables was assessed using widely recognised fit indices, including the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Incremental Fit Index (IFI), the Goodness-of-Fit Index (GFI) and the Root Mean Square Error of Approximation (RMSEA). These indices collectively evaluate the model's adequacy in representing the observed data. These indices are based on maximum likelihood estimation with continuous data, ensuring their suitability for this analysis.

Kline (2016) suggests that a relative chi-square (χ^2/df) value of less than 3 indicates an acceptable model fit, while some researchers, such as Schumacker and Lomax (2004), argue that values up to 5 may also be deemed acceptable. The CFI, which ranges from 0 to 1, measures the model's fit relative to a null model, with values close to 1 indicating a strong fit. A CFI value greater than 0.90 is generally considered acceptable, as it suggests that the model accounts for at least 90% of the covariation in the data (Fan et al., 1999). The TLI is also known as the Non-Normed Fit Index. Similar to other fit indices, a TLI value greater than 0.90 is indicative of an acceptable model fit (Schumacker and Lomax, 2004; Collier, 2020). The IFI ranges from 0 to 1, with values close to 1 indicating a strong model fit compared to a null model. An IFI value above 0.90 is considered acceptable, demonstrating substantial improvement over the null model (Bollen, 1989). The GFI measures how well the model fits the observed data, with values ranging from 0 to 1. A GFI value of ≥ 0.80 is generally acceptable, indicating that the model explains a substantial proportion of the variance (Jöreskog et al., 1984). The RMSEA measures "badness-of-fit," with lower values indicating better fit. Values below 0.05 represent good fit, 0.08 or below indicate adequate fit and values above 0.10 suggest poor fit (MacCallum et al., 1996). A 90% confidence interval accompanies RMSEA, offering additional insights into model acceptability. For instance, an RMSEA of 0.06 reflects an adequate fit.

Table 17 summarises these model fit thresholds, serving as a benchmark for evaluating the measurement model's adequacy. By adhering to these criteria, this study ensures the reliability and validity of its constructs, reinforcing the integrity of the theoretical framework underpinning the research. Thus, CFA not only validates the measurement model but also establishes a foundation for subsequent structural analyses.

Table 17. Goodness of fit (CFA)

Items	Initial Fit	Final Fit	Recommended values
CMIN/DF	1.528	1.446	≤ 3
CFI	0.891	0.919	≥ .90
IFI	0.896	0.923	≥ .90
TLI	0.869	0.900	≥ .90
RMSEA	0.067	0.062	≤ 0.08
GFI	0.776	0.800	≥ 0.8
PCLOSE	0.008	0.071	≥ .000

The evaluation of model fit through iterative refinement revealed notable improvements across key indices. To address these initial limitations, the model (Figure 8) was refined by first addressing low-factor loadings. Indicators with loadings below or close to 0.50 were removed to improve construct reliability and validity, as recommended by (Collier, 2020). The GOR1 indicator, which had a factor loading of 0.38, was removed first. This was followed by the deletion of the STR3 indicator, which carried a factor loading of 0.51. Subsequently, further refinement was guided by the modification indices for the default model. Error terms were covaried to account for unexplained correlations between certain items, beginning with e1 (AAT1) and e2 (AAT2). Additional error covariances were introduced between e8 (OGC2) and e9 (OGC3) and e29 (CEF2) and e30 (CEF3).

Table 18. Deleted indicators

Construct	Indicator	Factor loading	Measurement item
Government Regulation	GOR1	0.38	South African government regulations support the adoption of AI.
Skilled AI Technical Resources	STR3	0.51	My organisation can effectively recruit skilled AI professionals.

Following these refinements, the model Figure 9 demonstrated significant improvements across most indices, as seen in the final fit figures in Table 17. The model fit improved notably after refinement. The CMIN/DF decreased from 1.528 to 1.446, remaining within the acceptable threshold of ≤ 3. The CFI and IFI increased from 0.891 and 0.896 to 0.919 and 0.923, respectively, both exceeding the ≥ 0.90 threshold. The TLI improved from 0.869 to 0.900, meeting the minimum standard. The RMSEA decreased from 0.067 to 0.062, remaining within ≤ 0.08 and the GFI improved from 0.776 to 0.800, reaching the acceptable ≥ 0.80 cutoffs suggested by (Jöreskog et al., 1984). The PCLOSE value also rose from 0.008 to 0.071, further supporting the model's adequacy. These changes confirmed the model’s alignment with the observed data.

Overall, the iterative refinement process, including removing low-loading indicators and the covariance of error terms, transitioned the model from an adequate to a good overall fit. Most indices met or exceeded their respective thresholds, confirming the model’s ability to represent the data effectively. These results underscored the importance of a systematic approach to model refinement in achieving a robust and theoretically valid measurement model.

Figure 8 and Figure 9 present the graphical depictions of the measurement model, illustrating both the initial and refined versions, respectively, as generated using AMOS.

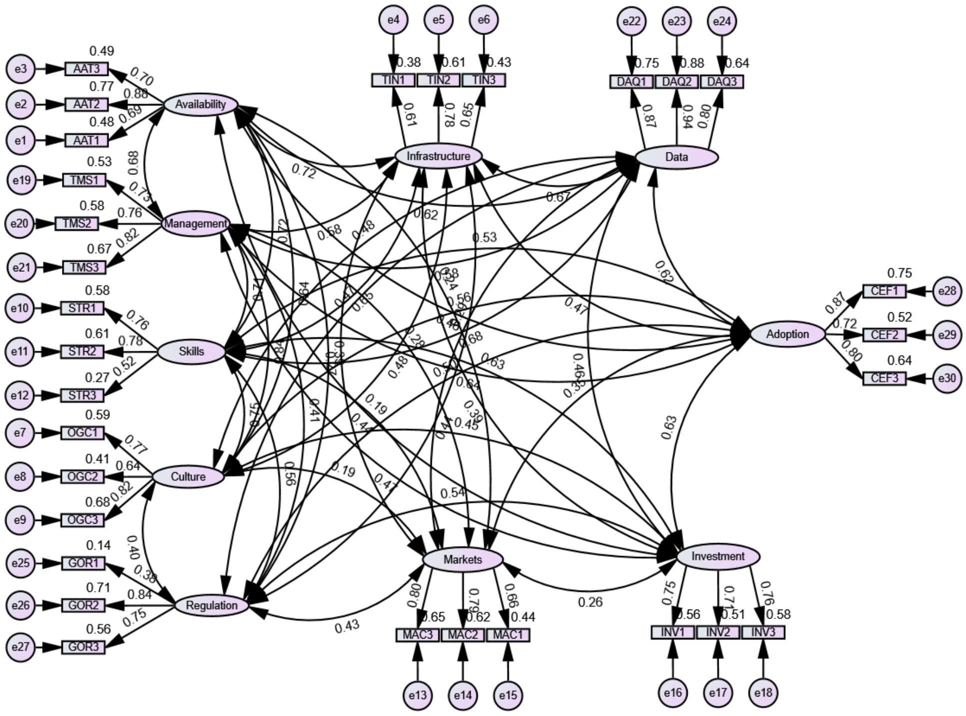

Figure 8. Initial measurement model

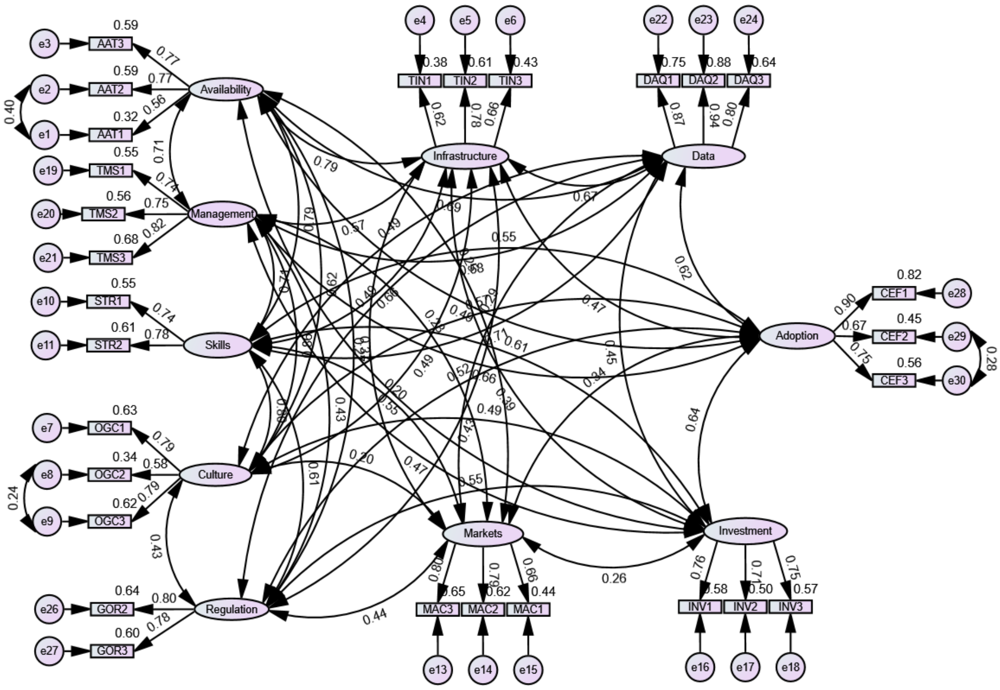

Figure 9. Improved measurement model

4.5.2 Reliability analysis

Reliability analysis is an essential step in ensuring that measurement instruments consistently and accurately capture the constructs they are intended to measure. Two key metrics for evaluating reliability are Cronbach's Alpha and Composite Reliability (CR).

Cronbach's Alpha, widely regarded as a foundational measure of internal consistency, assesses the extent to which items within a scale are interrelated. Pallant (2020) suggests that a Cronbach's alpha of ≥ 0.70 is acceptable, although values above 0.80 are preferable for robust reliability. This study followed Pallant’s (2020) recommendation and assessed internal consistency reliability using SPSS.

In addition to Cronbach's Alpha, CR is increasingly recognised for its ability to provide a more precise measure of internal consistency, especially in CFA and SEM. Hair et al. (2021) recommend assessing both Cronbach's Alpha and CR, as they represent the lower and upper bounds of reliability, respectively. For non-exploratory studies, a threshold of ≥ 0.70 is considered the minimum, while values exceeding 0.95 may indicate item redundancy, potentially undermining content validity. CR is calculated using the formula in Figure 10 below, where λi represents the factor loadings of the items and θi represents the error variances of the items (Hair et al., 2019).

$$CR = \frac{\left(\sum \lambda_i\right)^2}{\left(\sum \lambda_i\right)^2 + \sum \theta_i}$$

Figure 10. Composite Reliability (CR) formula

By employing both metrics, this study ensured a robust evaluation of internal consistency reliability, enhancing the validity and precision of the constructs used.

In this research, CR was evaluated using AMOS. The standardised regression weights extracted from AMOS were utilised in conjunction with the James Gaskin research toolkit (2016) to compute the CR values. The findings for both Cronbach's Alpha and Composite Reliability are summarised in Table 19.

Table 19 summarises the reliability analysis of the constructs, presenting Cronbach's Alpha (α) and Composite Reliability (CR) values. All constructs achieved satisfactory reliability, with Cronbach's Alpha values exceeding the recommended threshold of 0.70 (Pallant, 2020). DAQ and TMS demonstrated particularly strong reliability, with α values of 0.900 and 0.809, respectively. STR and GOR required the removal of one item each but retained acceptable reliability, with α values of 0.734 and 0.767, respectively.

The CR values further confirmed the constructs' reliability, with all exceeding the recommended minimum of 0.70 (Hair et al., 2021). DAQ and CEF showed strong CR values of 0.902 and 0.822, respectively. While AAT and TIN had slightly lower CR values of 0.747 and 0.727, these still met acceptable thresholds. Overall, the results indicated that the constructs are reliable and suitable for further analysis, with Cronbach's Alpha and CR providing robust evidence of internal consistency.

Table 19. Reliability using Cronbach's alpha

Items	Total items	Items after deleting	Cronbach's Alpha (α)	CR (Composite Reliability)
AAT	3	3	0.796	0.747
TIN	3	3	0.727	0.727
DAQ	3	3	0.900	0.902
TMS	3	3	0.809	0.815
STR	3	2 (STR3)	0.734	0.734
OGC	3	3	0.783	0.767
GOR	3	2 (GOR1)	0.767	0.769
MAC	3	3	0.793	0.796
INV	3	3	0.782	0.784
CEF	3	3	0.841	0.822

4.5.3 Convergent validity

Convergent validity assesses the extent to which multiple indicators of a construct correlate highly, demonstrating that they measure the same underlying concept. It is a key component of construct validity, ensuring that the observed variables effectively represent the latent variable they are designed to measure (Hair et al., 2019). The evaluation of convergent validity typically involves calculating the AVE, which quantifies the proportion of variance explained by a construct concerning the variance due to measurement error. An AVE value of ≥ 0.50 indicates adequate convergent validity, signifying that at least 50% of the variance in the indicators is attributable to the construct (Fornell and Larcker, 1981).

In this study, convergent validity was assessed using AMOS to obtain standardised factor loadings and error variances. These values were then used to calculate the AVE. This process ensures that the constructs demonstrate sufficient shared variance among their indicators, supporting the reliability and validity of the measurement model.

Table 20 presents the AVE values for assessing convergent validity, with most constructs meeting the ≥ 0.50 threshold (Fornell and Larcker, 1981). DAQ demonstrated particularly strong validity with an AVE of 0.755, followed by TMS and CEF, which showed adequate validity with AVE values of 0.595 and 0.610, respectively. STR, GOR and MAC also met the threshold, with AVE values ranging from 0.568 to 0.624.

AAT and OGC marginally met the threshold, with AVE values of 0.501 and 0.527, respectively. However, TIN fell slightly below the threshold, with an AVE of 0.473. Despite this, TIN was retained due to its CR of 0.727, which exceeded the acceptable benchmark of ≥ 0.70 (Hair et al., 2021). This proximity to the threshold and its acceptable CR justified its inclusion. If an AVE is slightly below 0.50, some researchers argue that it may still be acceptable if the CR is above 0.70, as CR provides an upper bound for reliability (Malhotra and Dash, 2011). Overall, the results indicate that the constructs exhibit robust convergent validity, with minor limitations in TIN noted for further refinement in future studies.

Table 20. Convergent validity using average variance extracted

Items	Initial items (Items retained)	AVE (Convergent Validity)
AAT	3(3)	0.501
TIN	3(3)	0.473
DAQ	3(3)	0.755
TMS	3(3)	0.595
STR	3(2)	0.580
OGC	3(3)	0.527
GOR	3(2)	0.624
MAC	3(3)	0.568
INV	3(3)	0.548
CEF	3(3)	0.610

4.5.4 Discriminant validity

Discriminant validity assesses whether a construct is sufficiently distinct from other constructs, ensuring that it measures a unique concept and not merely overlapping aspects of other variables (Fornell and Larcker, 1981). This validity is important for ensuring the measurement model is theoretically solid and for avoiding multicollinearity problems of two or more variables being too closely related in SEM, thus making it hard to determine their individual effects.

While traditional methods, such as the Fornell-Larcker criterion and cross-loadings, have been widely used, recent research highlights their limitations in reliably detecting discriminant validity issues (Henseler et al., 2015). As a more robust alternative, the Heterotrait-Monotrait Ratio (HTMT) has gained prominence for its ability to identify discriminant validity concerns with greater precision. Among the HTMT variants, HTMT2 is particularly valuable as it adjusts for measurement error, making it more rigorous and reliable in confirming discriminant validity, especially in studies involving reflective measurement models.

This study employed HTMT2 to ensure a thorough evaluation of discriminant validity, as its enhanced sensitivity and accuracy address the limitations of traditional approaches. HTMT2 was calculated using a correlation matrix generated with a tool developed by (Henseler, n.d.). The implied correlation values from AMOS were used to populate the matrix, enabling the computation of the final HTMT2 output. By adopting HTMT2, the study strengthens the reliability and validity of its constructs, ensuring robust results for subsequent analysis. Table 21 summarises the results of the assessment of discriminant validity.

Table 21. Discriminant validity using Heterotrait-Monotrait (HTMT)

HTMT2										
CEF										
GOR	0.499									
DAQ	0.593	0.488								
TMS	0.631	0.427	0.577							
INV	0.612	0.551	0.455	0.469						
MAC	0.331	0.438	0.288	0.278	0.262					
STR	0.531	0.609	0.712	0.708	0.613	0.201				
OGC	0.528	0.414	0.474	0.830	0.475	0.190	0.768			
TIN	0.454	0.428	0.666	0.571	0.389	0.274	0.659	0.475		
AAT	0.437	0.349	0.643	0.667	0.515	0.230	0.738	0.563	0.741	
	CEF	GOR	DAQ	TMS	INV	MAC	STR	OGC	TIN	AAT

4.6 Structural Model Analysis (SEM)

4.6.1 Structural model fit assessment

Table 22 shows that the structural model fit indicated an overall acceptable fit. The CMIN/DF was 1.446, falling within the ≤ 3 threshold and the GFI was 0.800, meeting the minimum acceptable value. Both the CFI (0.919) and IFI (0.923) exceeded the ≥ 0.90 cutoff, indicating a strong incremental fit. The TLI also met the threshold at 0.900 and the RMSEA was 0.062, remaining below the ≤ 0.08 limit, supported by the PCLOSE value of 0.071. These indices confirmed the model's suitability and reliability.

Table 22. Goodness of fit (SEM)

Items	Fit	Recommended values
CMIN/DF	1.446	≤ 3
GFI	0.800	≥ .80
CFI	0.919	≥ .90
IFI	0.923	≥ .90
TLI	0.900	≥ .90
PCLOSE	0.071	≥ 0.0
RMSEA	0.062	≤ 0.08

Figure 11 below presents the structural model with standardised path estimates, illustrating the relationships between technological, organisational, and environmental contexts and AI adoption for PPM.

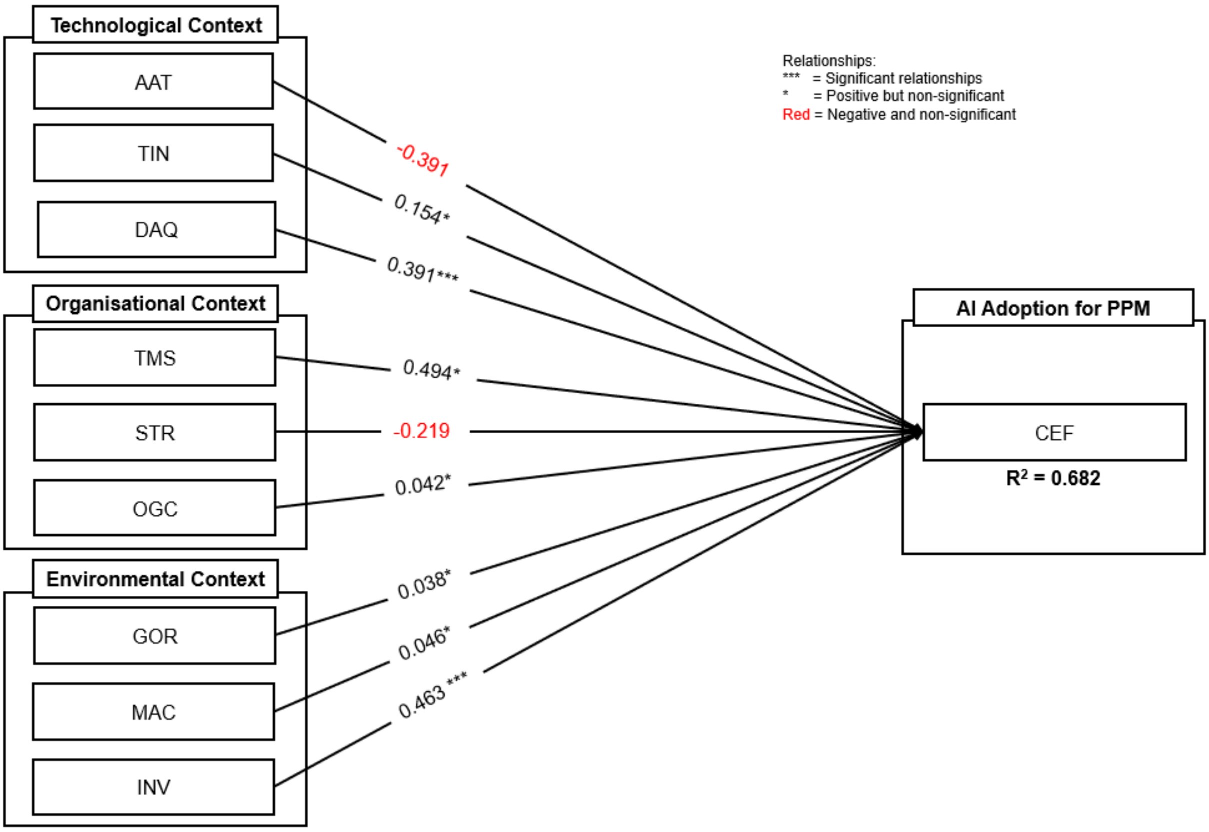

Figure 11. Structural model with standardised path estimates

4.7 Hypothesis testing

Table 23 summarises the results of the hypothesis testing conducted using AMOS. The final column specifies whether each hypothesis was empirically supported or not.

Table 23. Testing of the structural model relationships

Hypothesis	Path	Standardised Estimate	*t*-value	*p*-value	Decision
H1	AAT--->CEF	-0.391	-0.852	0.394	Not supported
H2	TIN--->CEF	0.154	0.648	0.517	Not supported
H3	DAQ--->CEF	0.391	2.127	0.033	Supported
H4	TMS--->CEF	0.494	1.164	0.245	Not supported
H5	STR--->CEF	-0.219	-0.379	0.705	Not supported
H6	OGC--->CEF	0.042	0.081	0.936	Not supported
H7	GOR--->CEF	0.038	0.163	0.870	Not supported
H8	MAC--->CEF	0.046	0.380	0.704	Not supported
H9	INV--->CEF	0.463	2.910	0.004	Supported

Note: AAT = Availability of AI technologies. TIN = Technological infrastructure. DAQ = Data quality. TMS = Top management support. STR = Skilled AI technical resources. OGC = Organisational culture. GOR = Government regulation. MAC = Market competition. INV = Investment conditions. CEF = TOE combined adoption effect.

Results of Hypothesis 1

Hypothesis 1 (H1): The availability of AI technologies is positively associated with the adoption of AI for PPM in South African financial services.

The analysis demonstrates that the availability of AI technologies has a negative and non-significant effect on AI adoption ($\beta = -0.391$, $p = 0.394$). This result indicates an inverse relationship, where higher availability of AI technologies is associated with lower adoption, though this relationship is not statistically significant. Consequently, H1 is rejected.

Results of Hypothesis 2

Hypothesis 2 (H2): The availability of a developed technological infrastructure is positively associated with the adoption of AI for PPM in South African financial services.

The analysis indicates that the availability of a developed technological infrastructure has a positive yet non-significant effect on AI adoption (β = 0.154, p = 0.517). This non-significant result implies that technological infrastructure does not play a substantial role in influencing AI adoption within this context. As a result, H2 is rejected.

Results of Hypothesis 3

Hypothesis 3 (H3): High data quality is positively associated with the adoption of AI for PPM in South African financial services.

The analysis reveals that high data quality has a positive and statistically significant effect on the adoption of AI (β = 0.391, p = 0.033). This finding indicates that as data quality improves, the likelihood of AI adoption increases, and the relationship is statistically significant. As a result, H3 is supported.

Results of Hypothesis 4

Hypothesis 4 (H4): Top management support is positively related to the adoption of AI for PPM in South African financial services.

The analysis shows that top management support has a positive but statistically non-significant impact on AI adoption (β = 0.494, p = 0.245). This result suggests that while top management support may have some influence, it does not apply a meaningful or statistically significant effect in this context. Therefore, H4 is rejected.

Results of Hypothesis 5

Hypothesis 5 (H5): The availability of skilled AI personnel is positively related to the adoption of AI for PPM in South African financial services.

The analysis demonstrates that the availability of skilled AI personnel has a negative and statistically non-significant effect on AI adoption (β = -0.219, p = 0.705). This result indicates an inverse relationship where, as the availability of skilled AI personnel increases, AI adoption decreases, though this relationship is not statistically significant. Thus, H5 is rejected.

Results of Hypothesis 6

Hypothesis 6 (H6): A supportive organisational culture is positively related to the adoption of AI for PPM in South African financial services.

The analysis reveals that a supportive organisational culture has a positive but statistically non-significant influence on the adoption of AI ($\beta = 0.042$, $p = 0.936$). This indicates that organisational culture does not exert a meaningful impact on AI adoption in this context. Thus, H6 is rejected.

Results of Hypothesis 7

Hypothesis 7 (H7): Supportive government regulation is positively associated with the adoption of AI for PPM in South African financial services.

The analysis demonstrates that supportive government regulation has a positive but statistically non-significant influence on AI adoption ($\beta = 0.038$, $p = 0.870$). This finding implies that, although supportive government regulation shows a positive effect, it does not significantly impact AI adoption in this context. Therefore, H7 is rejected.

Results of Hypothesis 8

Hypothesis 8 (H8): Increased market competition is positively related to the adoption of AI for PPM in South African financial services.

The analysis shows that increased market competition has a positive but statistically non-significant influence on AI adoption ($\beta = 0.046$, $p = 0.704$). This result suggests that while increased market competition might have a positive effect, it does not exert a meaningful or statistically significant impact in this context. As a result, H8 is rejected.

Results of Hypothesis 9

Hypothesis 9 (H9): Favourable investment conditions are positively associated with the adoption of AI for PPM in South African financial services.

The analysis indicates that favourable investment conditions have a positive and statistically significant influence on AI adoption ($\beta = 0.463$, $p = 0.004$). This relationship suggests that as favourable investment conditions improve, the likelihood of AI adoption increases. Consequently, H9 is supported.

4.7.1 Squared multiple correlation

The squared multiple correlation (R^2) for Adoption was 0.682, indicating that 68.2% of the variance in AI adoption was explained by the predictors in the model. This reflects a strong level of explanatory power, suggesting that the independent variables collectively have a significant impact on AI adoption. The remaining 31.8% of the variance is attributable to factors not included in the model.

4.8 Summary of the results

This chapter presented the results of the survey questionnaire using SEM to investigate the adoption of AI for PPM in South African financial services. Data screening ensured the integrity of the 118 valid responses retained for analysis, representing executives, IT and project management employees. Demographic analysis revealed a diverse participant profile, predominantly mid-career employees with meaningful experience. The measurement model was evaluated through CFA, confirming reliability, convergent validity and discriminant validity, with most constructs meeting the recommended thresholds.

The structural model demonstrated a good fit, with 68.2% of the variance in AI adoption explained by the predictors. Hypothesis testing identified high data quality and favourable investment conditions as significant positive drivers of AI adoption, while other factors such as AI availability, technological infrastructure and organisational culture were non-significant. These findings provide key insights into the drivers of AI adoption for PPM in financial services, highlighting critical areas for practical application and future research.

CHAPTER 5. DISCUSSION OF RESULTS

5.1 Introduction

This chapter discusses the study's findings regarding the research questions, which investigate the technological, organisational and environmental factors influencing the adoption of AI for PPM within South Africa's financial services sector. The discussion integrates the findings' results with relevant literature, providing insights into the study's significance and aligning the findings with existing research.

5.2 Discussion of the demographic profile of respondents

Respondents were predominantly mid-career IT and project management employees within South African financial services. Most were aged between 31 and 50 years, which is a demographic that typically holds leadership and strategic roles in organisations. This age group is often at the forefront of adopting and implementing new technologies, leveraging their accumulated experience and responsibility for driving innovation within their organisations (McKinsey, 2024). Research by Liang et al. (2021) further supports this, suggesting that individuals in this age group often play a pivotal role in bridging organisational strategy with technology adoption.

Over half of the respondents held postgraduate qualifications, indicating a highly educated and skilled workforce. Advanced technologies like AI demand strong technical, analytical and strategic competencies (Kumari et al., 2024; Davenport and Ronanki, 2018). This result aligns with findings from Schoeman et al. (2021), who emphasise that employees with advanced qualifications are better equipped to adapt to and maximise the potential of emerging technologies like AI. The high level of educational attainment among respondents suggests that South Africa's financial services sector recognises the importance of technical expertise in fostering innovation.

A significant proportion of respondents were directly involved in IT decision making, reflecting their active roles in evaluating, approving and implementing AI systems.

Decision-makers are crucial in determining the success of technology adoption, as they set priorities, allocate resources and ensure alignment with organisational goals (Liang et al., 2021). These findings show that the views in this study are practical and well-informed, making the insights more relevant to the broader adoption process.

Respondents were predominantly from the banking and insurance sectors. These sectors are historically characterised as early adopters of innovative technologies due to high competition and stringent regulatory requirements (Moore et al., 2021; Brynjolfsson and McAfee, 2017). These sectors face constant pressure to optimise operations, enhance customer experiences and maintain compliance, making them fertile ground for AI adoption. For instance, Toma (2023) highlights that competitive pressures and organisational readiness are key drivers for big data adoption in South Africa's banking sector.

South Africa's financial services sector is well-positioned for AI adoption, supported by an experienced, highly qualified workforce with decision making authority. However, the focus on banking and insurance reveals gaps in readiness among smaller, less-resourced sub-sectors. Targeted efforts to improve technological readiness are essential to ensure the entire sector benefits from AI-driven innovations.

5.3 Discussion of research question 1: Technological factors

Research question 1 aimed to identify the technological factors influencing the adoption of AI for PPM in South Africa's financial services sector. The analysis investigated three technological factors: availability of AI technologies, technological infrastructure and data quality.

5.3.1 Availability of AI technologies

The study hypothesised that the availability of AI technologies is positively associated with AI adoption. However, the findings revealed a negative and non-significant relationship ($\beta = -0.391$, $p = 0.394$) where higher availability of AI technologies is associated with lower adoption, indicating that the mere availability of AI tools does not guarantee their adoption. This finding aligns with studies such as those by Pumplun et al. (2019) and Abonamah and Abdelhamid (2024), which highlight that access to technology must be accompanied by organisational readiness, training and strategic alignment to achieve meaningful adoption. Challenges such as resistance to change, limited understanding of how AI technologies like ML or NLP can be effectively applied and misaligned organisational priorities often hinder the effective use of these tools.

Contrary perspectives, however, provide additional insights as described in the literature review in Chapter 2 where the availability of AI technologies positively supports adoption (Gupta et al., 2022; Kumari et al., 2024; Srinivasan et al., 2024). A recent study by Ahmadi (2024) noted that in organisations with strong leadership and well-defined strategic frameworks, the availability of AI technologies significantly drove adoption. Similarly, Mittal (2019) found that in financial planning, advanced AI tools encouraged adoption by enabling operational efficiencies and innovation.

These perspectives suggest that in the South African financial services context, availability alone is insufficient to drive adoption but can act as a catalyst when coupled with enablers such as strong governance, user competence and alignment with organisational objectives.

5.3.2 Technological infrastructure

The study also hypothesised that the availability of a developed technological infrastructure is positively associated AI adoption. The findings showed a positive but non-significant relationship ($\beta = 0.154$, $p = 0.517$), implying that technological infrastructure does not play a substantial role in influencing AI adoption within this context. The positive relationship aligns with the theoretical base literature review of Costa et al. (2022) and Mohammad (2022) who state that infrastructure is a key driver of AI adoption. While infrastructure provides the foundation for AI systems, this result suggests that infrastructure alone cannot guarantee successful adoption. This aligns with the findings by Chen and Tajdini (2024) and Schoeman et al. (2021), which indicates that infrastructure must be supported by strategic alignment, leadership commitment and skilled employees to translate potential into practice.

Infrastructure is vital in financial services, especially in banking and insurance, where robust IT systems manage complex operations and large data volumes. In a recent study, Kumari et al. (2024) note that infrastructure supports AI adoption when combined with supplier partnerships, financial resources and governance. In South Africa, gaps in readiness, particularly among smaller companies, highlight the need for targeted investments and vendor collaboration to enhance adoption.

5.3.3 Data quality

The study confirmed that high data quality has a positive and significant influence on AI adoption ($\beta = 0.391$, $p = 0.033$), indicating that as data quality improves, the likelihood of AI adoption increases. This finding highlights the critical role of reliable, accurate and consistent data in enabling AI systems to deliver trustworthy outputs and aligns with sentiments expressed in the theoretical base literature by Al-Khatib (2023), Costa et al. (2022) and Nguyen et al. (2022). High-quality data ensures operational accuracy and fosters trust in AI-driven decisions, promoting broader adoption within organisations.

These findings align with Ahmadi (2024) and Hentzen et al. (2022), who highlight that data quality is crucial for AI to interpret customer behaviour, optimise processes and support decision making. Kumari et al. (2024) emphasise that strong data governance ensures consistency and scalability in AI applications like ML and fraud detection. Keeping data quality high is important due to strict regulations and the risks involved in financial decisions, especially in the financial services sector of South Africa. Investing in data tools, audits and training can enhance AI performance, resulting in better efficiency, improved customer satisfaction and a stronger competitive edge.

5.4 Discussion of research question 2: Organisational factors

Research question 2 sought to explore the organisational factors influencing the adoption of AI for PPM in South Africa’s financial services sector. Three factors were analysed: top management support, the availability of skilled AI personnel and a supportive organisational culture.

5.4.1 Top management support

The hypothesis suggested that top management support would positively impact AI adoption. The results showed a positive but non-significant relationship ($\beta = 0.494$, $p = 0.245$), suggesting that while top management support may have some influence, it does not apply a meaningful or statistically significant effect in this context. This finding highlights that leadership commitment alone may not be enough to ensure AI adoption without additional supporting factors. Research by Chen and Lin (2023) and Kapoor et al. (2023) similarly shows that the effectiveness of top management depends on their ability to turn strategic priorities into action, allocate sufficient resources and promote a culture of innovation. These studies stress that leadership must go beyond words by taking visible steps, such as offering funding, training, and clear governance frameworks.

In South Africa's financial services sector, strict regulations and limited resources can reduce the impact of leadership on AI adoption. Smith et al. (2023) suggest that in resource-limited settings, leadership support needs to be combined with specific efforts to address challenges like meeting regulations and addressing skills shortages. This shows that while leadership is important, its impact is greatest when paired with strong organisational readiness and a clear strategy.

5.4.2 Availability of skilled AI personnel

The study hypothesised that skilled AI personnel would positively influence AI adoption. However, the findings revealed a negative and non-significant relationship ($\beta = -0.219$, $p = 0.705$). This non-significant inverse relationship implies that as the availability of skilled AI personnel increases, AI adoption decreases. While this contrasts with studies emphasising the critical role of human capital in technology adoption, it highlights the challenges faced in leveraging technical expertise effectively. Mughal et al. (2022) and Ahmed et al. (2023) underscore that skilled personnel are pivotal in adopting AI technologies such as ML and NLP, particularly when their expertise is utilised through well-structured roles, cross-functional collaboration and ongoing professional development.

These advanced technologies demand both technical expertise and alignment with organisational objectives. The findings indicate that South Africa's financial services sector struggles with issues like skill mismatches, insufficient training, and poorly aligned roles. Kapoor et al. (2023) emphasise that the potential of skilled AI professionals is maximised when organisations provide clear career paths, promote knowledge sharing and encourage innovation. Therefore, while skilled personnel are crucial for AI adoption, their effectiveness relies on how well their expertise is leveraged.

5.4.3 Organisational culture

The hypothesis that a supportive organisational culture positively influences AI adoption showed a positive but non-significant effect ($\beta = 0.042$, $p = 0.936$). This result indicates that while organisational culture can facilitate innovation, it may not directly drive AI adoption without other supporting factors, which can cause a meaningful impact. This is supported by Zhao and Wang (2022) and Kapoor et al. (2023) who argue that a culture fostering experimentation and collaboration must be aligned with leadership commitment and operational readiness to influence adoption meaningfully.

Hierarchical structures and a cautious approach to innovation can hinder the impact of supportive cultural practices in organisations, particularly in South Africa's financial services sector. Smith et al. (2023) highlight that fostering a culture conducive to AI adoption requires intentional efforts to overcome resistance, encourage collaboration and reward innovation. When combined with a clear vision and strategic goals, such a culture can significantly enhance an organisation's ability to adopt AI technologies effectively.

5.5 Discussion of research question 3: Environmental factors

Research question 3 examined how environmental factors influence the adoption of AI for PPM within South Africa's financial services sector. The study tested three hypotheses related to government regulation, market competition and investment conditions, providing important insights into their impact on AI adoption.

5.5.1 Government regulation

The study hypothesised that supportive government regulation would positively influence AI adoption. However, the results showed a positive but non-significant effect ($\beta = 0.038$, $p = 0.870$). This suggests that while regulatory frameworks create an enabling environment for AI adoption, they do not directly drive its implementation. This aligns with the literature review of Hanna et al. (2020) and Wang et al. (2024). Additionally, Kumar et al. (2023) and Chiarini et al. (2022) similarly noted that government policies often provide the foundation for innovation by mitigating risks and offering guidelines, but they rarely serve as the primary driver of adoption.

In South Africa, the Protection of Personal Information Act (POPIA) has a big impact on AI adoption. POPIA sets strict rules for data privacy and security, providing guidelines for using AI responsibly. While it helps ensure compliance, strict regulations can sometimes limit innovation, as Kaur and Swami (2022) suggest. To better support AI adoption, government policies should find a balance between enforcing rules and allowing flexibility so organisations can test and use AI technologies effectively.

5.5.2 Market competition

The analysis revealed a positive but non-significant relationship between market competition and AI adoption ($\beta = 0.046$, $p = 0.704$). While competitive pressures often motivate organisations to explore advanced technologies, this does not always translate into adoption unless accompanied by internal readiness. Similar findings were reported by Chen and Tajdini (2024), who noted that competitive environments act as catalysts for technological exploration but are insufficient without robust internal strategies and capabilities.

The financial services sector, particularly in banking and insurance, faces intense competition in South Africa, pushing organisations to innovate by improving efficiency and differentiating products. Ahmed et al. (2023) noted that companies often adopt technologies like ML, predictive analytics and chatbots to stay competitive. However, this adoption needs additional investments in infrastructure and skilled personnel; otherwise, the impact of competition on AI adoption may be limited.

5.5.3 Investment conditions

The study found that favourable investment conditions had a positive and significant influence on AI adoption ($\beta = 0.463$, $p = 0.004$), supporting Hypothesis 9, whose theoretical base was built from the literature review of Abdurrahman et al (2024), Dewi and Wiksuana (2023) and Al-Khatib (2023). This relationship suggests that as favourable investment conditions improve, the likelihood of AI adoption increases. This result highlights the critical role of financial resources in enabling organisations to invest in AI technologies. Studies by Ahmadi (2024), Kumari et al. (2024) and Zhang et al. (2023) similarly emphasise that access to funding, stable economic environments and financial incentives play essential roles in technology adoption.

Favourable investment conditions make it easier for organisations to acquire AI tools, hire skilled professionals and implement AI systems successfully. In South Africa's financial services sector, uneven access to investment opportunities can be a challenge, especially for smaller organisations. Larger companies with stronger financial backing are better positioned to adopt expensive technologies like ML, robotic process automation and NLP. Ahmed et al. (2023) highlight that economic stability and access to financing play a key role in encouraging the adoption of advanced technologies by reducing the risks tied to high costs.

5.6 Discussion of research question 4: Combined adoption effect on PPM

Research question 4 sought to evaluate the extent to which TOE factors collectively influence the adoption of AI for PPM within South Africa’s financial services sector. This integrated approach acknowledges that AI adoption is not driven by isolated factors but by the interplay of multiple influences.

The combined effect of TOE factors shows that technological, organisational and environmental readiness must work together to ensure successful AI adoption in PPM. Technological readiness provides the tools and systems needed, organisational readiness brings leadership and skilled staff to align AI with goals and environmental readiness adds support through regulations and market conditions. High-quality data is a key part of technological readiness. AI tools like ML rely on accurate data to provide insights that improve risk management, resource allocation and decision making for PPM. The study by Odejide and Edunjobi (2024) supports the complementary effect of these factors and states that AI's ability to analyse large datasets helps identify risks early and suggest proactive solutions, reducing delays and keeping contingency plans effective. Organisational support, including strong leadership and skilled staff, is important to ensure AI adoption fits with PPM goals. Investments in technology and training also play a big role in successful implementation. Finally, external factors like regulatory frameworks and market competition create a supportive environment to help unlock AI's full potential in South Africa's financial services sector (Kumari et al., 2024).

5.7 Summary of the discussion of results

The demographic profile revealed a skilled, mid-career workforce in leadership roles well-suited to advancing AI adoption. Among technological factors, high data quality stood out as a key enabler, while the availability of AI technologies and infrastructure required organisational readiness to be effective. Organisational factors like leadership support, skilled personnel and a culture of innovation showed limited direct impact without the contribution of other factors. Environmental factors, especially favourable investment conditions, played a crucial role, while government regulation and market competition had more indirect effects. These findings emphasise the importance of adopting a comprehensive approach to utilising AI for PPM in the sector.

CHAPTER 6. CONCLUSION and RECOMMENDATIONS

6.1 Introduction

This chapter provides a summary of the study's key findings, outlines its theoretical and contextual contributions and presents practical implications. It also highlights the study's limitations and offers recommendations for future research.

6.2 Research summary

This study explored four key questions related to adopting AI for PPM in the South African financial services sector. These questions focused on the technological, organisational and environmental factors that influence the adoption of AI and their combined impact. To answer these questions, nine factors were identified using the TOE framework and insights from existing literature. The data was collected through a cross-sectional survey of IT and project management professionals. A total of 118 valid responses were analysed.

The study found that data quality and a supportive investment environment are the most important factors influencing the adoption of AI. Organisations with reliable and accurate data were better positioned to adopt AI successfully. Similarly, investment conditions, including sufficient resources and favourable policies, played a crucial role in adopting AI.

Other factors, such as top management support, organisational readiness and technological infrastructure, showed positive but non-significant correlations with AI adoption. These results suggest that while these factors contribute to a broader environment for AI adoption, their influence may be indirect or dependent on other factors. For instance, top management support lays the groundwork for aligning AI initiatives with strategic objectives, while technological infrastructure ensures the necessary systems for effective AI implementation are in place. Together, these elements reflect the complex interplay of factors required to adopt AI for PPM successfully.

These findings underscore the need for organisations to focus on both internal readiness and external opportunities to integrate AI effectively into their PPM processes.

6.3 Theoretical contributions

This study has made several important theoretical contributions to the literature on AI adoption for PPM, particularly in the South African financial services sector.

First, this study contributes to academic research by addressing a gap in the literature on AI adoption for PPM in emerging markets. Most existing research has focused on developed economies and offers limited insights into the unique challenges and opportunities in South Africa. By applying the TOE framework, this study provides new insights into the specific technological, organisational and environmental factors influencing the adoption of AI in the South African financial services sector.

Secondly, this study has applied the TOE framework to the context of AI adoption for PPM, an area with limited prior research. The study demonstrates how data quality and investment conditions can be operationalised to examine adoption in a complex organisational context. By applying these concepts, the study extends the theoretical understanding of technology adoption processes in niche areas such as PPM.

Third, the study applies theoretical frameworks on technology adoption to explore how AI technologies, such as machine learning, deep learning, generative AI and predictive analytics, enhance PPM practices. This extends the applicability of these frameworks by linking them to real-world applications in PPM and providing insights into how organisations can improve their decision making and operational efficiency through AI.

Finally, this study contributes to the broader literature on technology adoption in emerging markets by considering the role of regional economic, social and organisational factors. For example, the results show how infrastructure constraints, regulatory policies and investment challenges influence the adoption process. This research enriches the global discourse on AI adoption and provides a basis for future studies in similar contexts.

Overall, these theoretical contributions deepen our understanding of AI adoption and its impact on organisations operating in resource-constrained and competitive environments.

6.4 Contextual contributions

This study makes three important contextual contributions to understanding the adoption of AI in the South African financial services sector.

First, it highlights the dual nature of the South African financial services sector, which consists of sophisticated institutions alongside smaller, resource-constrained organisations. Larger institutions like major banks and insurance companies benefit from access to cutting-edge technologies and skilled professionals. In contrast, smaller financial service providers often face challenges such as outdated infrastructure and a lack of skilled personnel. This duality underscores the importance of developing targeted strategies that consider differences in readiness and capacity for AI adoption.

Secondly, this study highlights the critical role of regulatory frameworks and government initiatives in shaping the AI landscape. South African regulators, such as the South African Reserve Bank, have taken steps to encourage innovation and ensure compliance in the financial sector. However, inconsistent enforcement and gaps in policy clarity pose challenges for organisations trying to integrate AI. These findings highlight the need for a more coherent and supportive regulatory environment to facilitate technology adoption.

Thirdly, the study shows how socio-economic factors influence the adoption of AI in South Africa. The high cost of implementation remains a significant barrier for many smaller organisations. Despite these challenges, competition within the sector is driving innovation. Some institutions prioritise AI to increase efficiency, improve the customer experience and remain competitive in a rapidly evolving market.

By focusing on these unique South African characteristics, this study provides valuable insights that can help policymakers, financial services leaders and researchers address the barriers to AI adoption and capitalise on the opportunities for innovation in the financial services sector.

6.5 Implications for practice

This study has shown that adopting AI offers significant opportunities to improve PPM practises in the South African financial services sector. The findings highlight several actionable implications.

The study has demonstrated the importance of targeted training for mid-career IT and project management professionals, who play a central role in decision making and innovation. AI tools can streamline project selection and resource allocation for project managers and enable more precise alignment with business objectives. IT leaders and professionals must focus on developing the technical infrastructure and data management systems required to support these tools effectively. By equipping these roles with the necessary technical and strategic skills, they can more successfully drive AI initiatives and ensure a data-driven approach to decision making.

The findings highlight the need to embed AI adoption strategies within broader organisational objectives. The study showed that AI tools can significantly improve project selection by analysing complex data sets to identify projects with the highest potential return on investment (ROI). For project managers, this means more informed prioritisation of high-impact initiatives. IT leaders play a critical role in ensuring that these tools integrate seamlessly with existing systems while aligning with business strategies. Integrating AI into PPM frameworks ensures that critical financial services functions such as customer relationship management, fraud detection and regulatory compliance are performed more effectively.

Operational efficiency in the financial services sector also benefits from AI adoption. This study has shown how AI adoption can improve project tracking, optimise resource deployment and automate reporting. Project managers can use these systems to monitor progress and proactively mitigate risks, while IT professionals ensure the robustness and scalability of the underlying technology. The banking and insurance sector is well positioned as leaders in technology adoption to guide smaller organisations by sharing best practices and facilitating industry-wide collaboration. Standardising AI applications across the industry can ensure consistent outcomes and drive innovation.

Ensuring high data quality and favourable investment conditions is fundamental to the effective adoption of AI. This study has shown that reliable data underpins AI performance and enables accurate decision making and operational improvements. PPM teams must prioritise robust data management to support AI-driven insights for project prioritisation and performance evaluation. IT leaders play a central role in creating and maintaining these governance structures, while project managers can leverage high-quality data to improve decision making across portfolios. In addition, targeted investment in AI tools and infrastructure is essential to increase and maintain adoption.

Valuable lessons can be learned from this study for factors that did not significantly influence the adoption of AI. The non-significant role of top management support suggests that leadership needs to actively translate strategic priorities into actionable steps, such as providing resources and fostering a culture of innovation. While the availability of skilled AI personnel did not have a direct impact, this study did highlight the importance of leveraging expertise through better role allocation, ongoing training and cross-functional collaboration. Technology infrastructure, while insignificant, remains a foundational element and should be strengthened through partnerships with vendors and targeted investment to close readiness gaps.

This study has shown that by addressing these priorities, the South African financial services sector can support the adoption of AI, improve PPM practices and ensure the efficient delivery of critical financial services functions. These steps will help project managers, IT leaders and IT professionals maintain a competitive edge in a rapidly evolving technological environment.

6.6 Limitations

While this study provides valuable insights into the adoption of AI for PPM in South African financial services, it is not without limitations.

First, at the time of the literature review, the use of AI for PPM in South Africa was still emerging, with limited academic literature available locally. Consequently, international studies and industry reports were relied upon and supplemented by insights from local experts. This reliance on global sources may limit the study's context-specific relevance.

Second, some journals consulted during the literature review were either not highly ranked or published more than three years ago. While these sources provided foundational knowledge and context, their lower rankings or age may mean they lack the most up-to-date insights or fail to reflect recent advancements in the field. This could limit the relevance of some theoretical underpinnings, especially in a rapidly evolving area such as AI adoption.

Third, the study used non-probability sampling with a snowballing method, leading to a concentration of responses from banking and insurance employees, who accounted for 66.1% of the sample. This focus may have excluded smaller or less-represented organisations.

Fourth, although the final sample size of 150, representing a 39.89% response rate, is considered reasonable for online surveys, as studies in the information technology field report an average response rate of approximately 41.22% as highlighted by Taherdoost and Madanchian (2023), it may still limit the generalisability of the findings to the wider financial services sector.

Fifth, outlier detection was not performed, as justified in Chapter 4, to preserve data integrity and retain potentially meaningful variations. However, this omission may have constrained the ability to identify anomalous patterns that could influence the results.

Sixth, the structured survey format, with fixed response options, restricted the depth of data collected, as it did not allow respondents to address their unique organisational contexts or challenges fully. In addition, the study's cross-sectional design limited the ability to capture the dynamic nature of AI adoption over time, providing only a snapshot of the current state.

Seventh, the technological infrastructure (TIN) construct showed limitations in its design, with a convergent validity of 0.473, below the acceptable threshold of 0.5 (Hair et al., 2019). This suggests that the construct may not fully capture the underlying aspects of technological infrastructure relevant to AI adoption.

Finally, the conceptual model does not include a moderating factor for organisational readiness for change, which may influence the relationship between TOE factors and AI adoption for PPM. Organisational readiness, including leadership commitment and openness to change, is critical for successful implementation. Its absence assumes uniform adoption outcomes, overlooking variability in organisational preparedness.

6.7 Future research directions

As AI adoption in PPM evolves in South Africa, researchers could focus on local case studies to build context-specific literature. Studies could examine how smaller financial institutions, such as credit unions or microfinance providers, navigate challenges like limited infrastructure or regulatory constraints.

Future studies should prioritise using recent, high-ranking academic sources to ensure theoretical frameworks reflect the latest advancements. Combining academic research with updated industry reports, such as Gartner's annual "Top Strategic Technology Trends" or McKinsey's "Global AI Adoption Index," could provide depth and practical relevance.

Incorporating outlier detection techniques would allow researchers to identify and analyse anomalous patterns, thereby strengthening the robustness of data analysis. For instance, statistical or machine learning methods could uncover organisations adopting AI unusually fast or facing significant barriers. Qualitative research could then explore these anomalies in detail to uncover underlying factors or unique strategies.

A mixed-methods approach, including qualitative interviews or focus groups, could provide richer insights into organisational challenges and specific contexts influencing AI adoption. Interviews could be conducted with key stakeholders such as senior executives, project portfolio managers, IT leaders and AI specialists, as they possess strategic, operational and technical insights into AI adoption processes. Engaging these participants would allow researchers to capture nuanced perspectives on leadership, organisational culture and resistance to AI adoption that may not emerge in structured survey responses.

Longitudinal studies would provide valuable insights into the dynamic nature of AI adoption over time. Tracking organisations for several years could reveal patterns in how AI capabilities evolve, how external factors influence adoption and the long-term impact on project outcomes.

An adapted TOE framework could be improved by adding constructs that focus on responsible and ethical AI adoption. For example, researchers could include a construct on "AI Governance and Ethics" to explore factors like transparency, fairness, accountability and reducing bias in AI systems. This could cover things like company policies on ethical AI, following regulatory guidelines, ways to manage bias in AI outputs and ensuring AI use aligns with societal values. In addition, combining TOE with models like the Unified Theory of Acceptance and Use of Technology (UTAUT) or the Diffusion of Innovation (DOI) theory would create a more complete framework. This combination would capture TOE and human factors, as well as the process of AI adoption over time. Such an approach allows for a well-rounded analysis of AI adoption, considering both ethical issues and the different factors that influence how organisations adopt new technology.

Leadership and skills-related factors warrant further investigation, as this study showed no significant impact. Understanding how leadership styles, effective training programmes and cultural change initiatives can foster AI readiness could provide actionable insights for organisations.

Moreover, while this study focused on AI adoption broadly, future research could explore specific AI applications, such as predictive analytics, robotic process automation (RPA) and natural language processing (NLP), to understand their unique contributions to decision making, resource optimisation and project outcomes.

Adding a moderating factor, such as organisational readiness for change, could improve the measurement model in SEM. This would capture how readiness influences the relationships between TOE factors and AI adoption for PPM. Including elements like leadership commitment and openness to change could enhance the model's validity and provide more precise insights into adoption variability.

Refining the technological infrastructure (TIN) construct could improve its ability to measure infrastructure readiness. Future research could expand the construct to include scalability, system integration and interoperability. Examining how organisations with legacy systems adapt their infrastructure for AI would provide actionable insights.

6.8 Conclusion

This study highlights the transformative potential of AI in PPM within South Africa's financial services sector. It adds insights to the growing literature on AI adoption by examining the TOE factors influencing adoption. The findings validate the importance of data quality and favourable investment conditions as critical enablers and offer theoretical and practical insights that enrich our understanding of how AI can be successfully integrated into organisational processes to enhance operational efficiency, improve strategic alignment and deliver better ROI. While challenges such as skills shortages and infrastructure limitations persist, the study demonstrates how the interplay of TOE factors can help organisations overcome these barriers and unlock the potential of AI.

Looking ahead, adopting AI offers immense opportunities for South Africa's financial services sector. Embracing AI is not just a means to improve efficiency but also a chance to gain strategic advantages and drive innovation. There is also a unique opportunity to harness AI responsibly and ethically, ensuring it aligns with organisational values, supports long-term business goals and contributes to broader societal goals. This study encourages stakeholders to envision a future where AI drives sustainable success and delivers meaningful impact within organisations.

REFERENCES

Abdurrahman, A., Gustomo, A., & Prasetio, E. A. (2024). Impact of dynamic capabilities on digital transformation and innovation to improve banking performance: A TOE framework study. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(1), 100215. https://doi.org/10.1016/j.joitmc.2024.100215

Abonamah, A. A., & Abdelhamid, N. (2024). Managerial insights for AI/ML implementation: A playbook for successful organizational integration. *Discover Artificial Intelligence*, *2*(22). https://doi.org/10.1007/s44163-023-00100-5

Adams, R. (2020). *Project Portfolio Management*. Project Management. https://www.projectmanagement.com/

Aguinis, H., Gottfredson, R. K., & Joo, H. (2013). Best-Practice Recommendations for Defining, Identifying, and Handling Outliers. *Organizational Research Methods*, *16*(2), 270–301. https://doi.org/10.1177/1094428112470848

Ahmadi, S. (2024). A comprehensive study on integration of Big Data and AI in financial industry and its effect on present and future opportunities. *International Journal of Current Science Research and Review*, *7*(1), 66–74.

Ahmed, S., Bhatti, A., & Hussain, M. (2023). The role of human capital in technology adoption: Evidence from emerging economies. *Journal of Innovation Management*, *11*(2), 101–117. https://doi.org/10.1108/jim-11-2022-0076

Ajigini, O. A., & Chinamasa, T. J. W. (2023). Modelling digital transformation within the financial sector: A South African perspective. *Information Resources Management Journal*, *36*(1), 1–14. https://doi.org/10.4018/irmj-320642

Al-Khatib, A. (2023). Drivers of generative artificial intelligence to fostering exploitative and exploratory innovation: A TOE framework. *Technology in Society*, *75*, 102403. https://doi.org/10.1016/j.techsoc.2023.102403

An, M., Lin, J., & Luo, X. (Robert). (2024). The impact of human AI skills on organizational innovation: The moderating role of digital organizational culture. *Journal of Business Research*, *182*, 114786. https://doi.org/10.1016/j.jbusres.2024.114786

Aniceski, T. A., Miranda, L. T. P., Canciglieri Junior, O., & Benitez, G. B. (2024). The Four Smarts of Industry 4.0 and barriers for technology deployment: A TOE perspective. *Computers and Industrial Engineering*, *193*, 110345. https://doi.org/10.1016/j.cie.2024.110345

Baabdullah, A. M. (2024). The precursors of AI adoption in business: Towards an efficient decision-making and functional performance. *International Journal of Information Management*, *75*, 102745. https://doi.org/10.1016/j.ijinfomgt.2023.102745

Badghish, S., & Soomro, Dr. Y. (2024). Artificial Intelligence Adoption by SMEs to Achieve Sustainable Business Performance: Application of Technology–Organization–Environment Framework. *Sustainability*, *16*, 1864. https://doi.org/10.3390/su16051864

Baker, J. (2012). The Technology–Organization–Environment Framework. In Y. K. Dwivedi, M. R. Wade, and S. L. Schneberger (Eds.), *Information Systems Theory* (Vol. 28, pp. 231–245). Springer New York. https://doi.org/10.1007/978-1-4419-6108-2_12

Bell, E., Bryman, A., & Harley, B. (2019). *Business Research Methods* (5th ed.). Oxford University Press.

Bhattacherjee, A. (2012). *Social science research: Principles, methods, and practices* (Second edition). Anol Bhattacherjee. https://scholarcommons.usf.edu/oa_textbooks/3/

Bollen, K. A. (1989). A New Incremental Fit Index for General Structural Equation Models. *Sociological Methods and Research*, *17*(3), 303–316. https://doi.org/10.1177/0049124189017003004

Brynjolfsson, E., & McAfee, A. (2017). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton and Company.

Byrne, B. (2016). *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming* (3rd.). Routledge. https://doi.org/10.4324/9781315757421

Čančer, V., Tominc, P., and Rožman, M. (2023). Multi-Criteria Measurement of AI Support to Project Management. *IEEE Access*, *11*, 142816–142828. https://doi.org/10.1109/ACCESS.2023.3342276

Chen, J., & Tajdini, S. (2024). A moderated model of artificial intelligence adoption in firms and its effects on their performance. *Information Technology and Management*, *25*(2), 123–140. https://doi.org/10.1007/s10799-024-00422-5

Chen, X., & Lin, Z. (2023). Leadership and AI adoption: Strategic priorities and organisational readiness. *Technology in Society*, *72*, Article 102241. https://doi.org/10.1016/j.techsoc.2023.102241

Chiarini, A., Belvedere, V., & Grando, A. (2022). The influence of government regulations on the adoption of artificial intelligence in industrial settings. *Technological Forecasting and Social Change*, *182*(121824).

Chukwuere, J. E., Mavetera, N., & Chukwuere, P. C. (2017). The effectiveness of WhatsApp in distributed survey research in academia: A case of South African university students. *Mediterranean Journal of Social Sciences*, *8*(5), 145–152. https://doi.org/10.2478/mjss-2017-0033

Cochran, W. (1977). *Sampling Techniques* (Third). John Wiley and Sons Inc.

Collier, J. E. (2020). *Applied Structural Equation Modeling Using AMOS: Basic to Advanced Techniques* (1st ed.). Routledge. https://doi.org/10.4324/9781003018414

Costa, R. L. D., Cruz, M., Gonçalves, R., Dias, Á., Silva, R. V. D., & Pereira, L. (2022). Artificial intelligence and its adoption in financial services. *International Journal of Services Operations and Informatics*, *12*(1), 70. https://doi.org/10.1504/IJSOI.2022.123569

Creswell, J. W. (2014). *Educational research: Planning, conducting and evaluating quantitative and qualitative research* (Pearson new international edition, fourth edition). Pearson.

Davenport, T., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, *96*(1), 108–116.

Deloitte. (2020). *Project Portfolio Management(PPM) in a digital world*. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/strategy/us-project-portfolio-mgmt-ppm-in-a-digital-world.pdf

Deloitte. (2022). *How Artificial Intelligence is Transforming the Financial Services Industry*. https://www.deloitte.com/content/dam/assets-zone1/ng/en/docs/services/risk-advisory/2023/ng-how-artificial-Intelligence-is-Transforming-the-Financial-Services-Industry.pdf

Dewi, S. K. S., & Wiksuana, I. G. B. (2023). The Role of Digital Financial Services on the Performance of MSMES in Indonesia using the Toe Model. *Migration Letters*, *20*(6), 723–737. https://doi.org/10.59670/ml.v20i6.3519

Evans, J. R., & Mathur, A. (2018). The value of online surveys: Advantages and disadvantages. Journal of Internet Research. *Journal of Internet Research*, *28*(4), 431–450. https://doi.org/10.1108/JIR-04-2018-0096

Fan, X., Thompson, B., & Wang, L. (1999). Effects of sample size, estimation methods, and model specification on structural equation modeling fit indexes. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 56–83. https://doi.org/10.1080/10705519909540119

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Gaffley, M. (2021). *AI and data in South Africa’s finance sector: Toward financial inclusion*. https://policyaction.org.za/sites/default/files/PAN_TopicalGuide_AIData9_FinServices_V1_Elec.pdf

Gaskin, J. (2016). *Stats Tools Package*. http://statwiki.gaskination.com

George, D., & Mallery, P. (2003). SPSS for Windows Step-by-Step: A Simple Guide and Reference, 14.0 update (7th Edition). *Http://Lst-Iiep.Iiep-Unesco.Org/Cgi-Bin/Wwwi32.Exe/[In=epidoc1.in]/?T2000=026564/(100)*.

Greener, S. (2008). *Business research methods*. Dr. Sue Greener and Vent us Publishing.

Gupta, S., Ghardallou, W., Pandey, D. K., and Sahu, G. P. (2022). Artificial intelligence adoption in the insurance industry: Evidence using the technology–organization–environment framework. *Research in International Business and Finance*, *63*, 101757. https://doi.org/10.1016/j.ribaf.2022.101757

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis*. Cengage. https://books.google.co.za/books?id=0R9ZswEACAAJ

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., and Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hair, J. F., & Sarstedt, M. (2019). Factors versus Composites: Guidelines for Choosing the Right Structural Equation Modeling Method. *Project Management Journal*, *50*(6), 619–624. https://doi.org/10.1177/8756972819882132

Hanna, Hany., Haroun, Mai. H., and Gohar, N. (2020). Developing a framework for blockchain adoption using TOE model. *Journal of Business and Retail Management Research*, *15*(01). https://doi.org/10.24052/JBRMR/V15IS01/ART-02

Henseler, J. (n.d.). *Heterotrait-monotrait ratio of correlations*. Retrieved 4 January 2025, from https://www.henseler.com/htmt.html

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hentzen, J. K., Hoffmann, A., Dolan, R., & Pala, E. (2022). Artificial intelligence in customer-facing financial services: A systematic literature review and agenda for future research. *International Journal of Bank Marketing*, *40*(6), 1299–1336. https://doi.org/10.1108/ijbm-09-2021-0417

IT Web. (2024). *Google study shows spike in South Africans' interest in AI*. https://www.itweb.co.za/article/google-study-shows-spike-in-south-africans-interest-in-ai/dgp45qaBOgKvX9l8

Johnson, B. (2018, August 30). Artificial Intelligence (AI)—Top Use Cases and Technologies Used Today. *Medium*. https://medium.com/@Brian.johnson_62680/artificial-intelligence-ai-top-use-cases-and-technologies-used-today-3c22e1a63e78

Jöreskog, K. G., Sörbom, D., & Magidson, J. (1984). *Advances in factor analysis and structural equation models*.

Kapoor, R., Malhotra, P., & Goyal, N. (2023). Bridging the AI skills gap in financial services: Challenges and solutions. *Journal of Financial Technology*, *4*(3), 245–267. https://doi.org/10.1057/s41599-023-00123-8

Kaur, J., & Swami, S. (2022). Economic incentives and AI adoption in financial services: Policy implications. *Policy and Technology Journal*, *14*(4), 378–392. https://doi.org/10.1016/j.ptj.2022.09.002

Kenton, W. (2021). *Financial Sector: Definition, Examples, Importance to Economy*. Investopedia. https://www.investopedia.com/terms/f/financial_sector.asp

Kestenholz, P. (2023). *Council Post: How AI Is Revolutionizing Project Management: Three Use Cases*. Forbes. https://www.forbes.com/sites/forbestechcouncil/2023/03/30/how-ai-is-revolutionizing-project-management-three-use-cases/

Khalid, A. H., Sapry, H. R., Jaafar, J., & Ahmad, A. R. (2024). The application of technology organization environment framework in the approaches for smart warehouse adoption. *In Advances in Business Management Research*, 91–101. https://doi.org/10.1007/978-3-031-47727-0_7

Kline, R. B. (2016). Principles and Practice of Structural Equation Modeling. *Guilford Press*. https://search.ebscohost.com/login.aspx?direct=trueandscope=siteanddb=nlebkanddb=nlabkandAN=1078917

Kumar, R., Singh, M., & Gupta, N. (2023). The role of government policy in the adoption of emerging technologies: Evidence from developing economies. *Journal of Public Administration and Policy Research*, *15*(1), 25–39. https://doi.org/10.1108/jpapr-03-2023-0056

Kumari, B., Kaur, J., & Swami, S. (2024). Adoption of artificial intelligence in financial services: A policy framework. *Journal of Science and Technology Policy Management*, *15*(2), 396–417. https://doi.org/10.1108/JSTPM-03-2022-0062

Lappalainen, L., Aleem, M., & Sandberg, B. (2023). How to manage open innovation projects? An integrative framework. *Project Leadership and Society*, *4*, 100095. https://doi.org/10.1016/j.plas.2023.100095

Liang, T. P., Liu, M. J., & Wu, C. H. (2021). Can executives' decision-making styles influence the success of artificial intelligence adoption? *Journal of Business Research*, *123*, 174–185. https://doi.org/10.1016/j.jbusres.2020.09.051

Light, M. (2024). *How AI assistants will help PPM 'Grandmasters' execute strategy*. Planisware. https://planisware.com/sites/default/files/2024-03/How%20AI%20Assisstants%20Will%20Help%20PPM%20Grandmasters%20Execute%20Strategy.pdf

Lohr, S. L. (2009). *Sampling: Design and Analysis* (2nd ed.). Richard Stratton.

Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management and Data Systems*, *111*(7), 1006–1023. https://doi.org/10.1108/02635571111161262

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power Analysis and Determination of Sample Size for Covariance Structure Modeling. *Psychological Methods*, *1*, 130–149. https://doi.org/10.1037/1082-989X.1.2.130

Maduku, D. K., Mpinganjira, M., & Duh, H. (2016). Understanding mobile banking adoption intention in South Africa: A multi-perspective framework. *International Journal of Bank Marketing*, *34*(7), 1038–1056. https://doi.org/10.1108/IJBM-03-2015-0038

Makanyeza, C., & Mutambayashata, S. (2018). Consumers' acceptance and use of plastic money in Harare, Zimbabwe: Application of the unified theory of acceptance and use of technology. *International Journal of Bank Marketing*, *36*(2), 379–392. https://doi.org/10.1108/IJBM-03-2017-0044

Malhotra, N. K., & Dash, S. (2011). *Marketing Research an Applied Orientation*. Pearson Publishing.

Malinga, S. (2024, March 18). *Big-four banks take lead in SA's GenAI, AI deployments*. ITWeb. https://www.itweb.co.za/article/big-four-banks-take-lead-in-sas-genai-ai-deployments/G98YdqLGK9pMX2PD

Mallek, L. (2024). *Program management vs. Project management*. Atlassian. https://www.atlassian.com/agile/project-management/program-management

Maragno, G., Tangi, L., Gastaldi, L., & Benedetti, M. (2023). Exploring the factors, affordances and constraints outlining the implementation of Artificial Intelligence in public sector organizations. *International Journal of Information Management*, *73*, 102686. https://doi.org/10.1016/j.ijinfomgt.2023.102686

Martinsuo, M., & Geraldi, J. (2020). Management of project portfolios: Relationships of project portfolios with their contexts. *International Journal of Project Management*, *38*(7), 441–453. https://doi.org/10.1016/j.ijproman.2020.02.002

Matsepe, N. T., & Van Der Lingen, E. (2022). Determinants of emerging technologies adoption in the South African financial sector. *South African Journal of Business Management*, *53*(1). https://doi.org/10.4102/sajbm.v53i1.2493

McCarthy, J., Minsky, M. L., Rochester, N., Corporation, I. B. M., & Shannon, C. E. (1955). *A proposal for the Dartmouth summer research project on artificial intelligence*.

McKinsey. (2024). *The state of AI in early 2024: Gen AI adoption spikes and starts to generate value*. McKinsey Global Publishing. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

McKinsey & Company. (2023). *Active portfolio management: Five practical insights for value creation*. https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/active-portfolio-management-five-practical-insights-for-value-creation

McKinsey & Company. (2024). What is AI (artificial intelligence)? *McKinsey Global Publishing*. https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-ai

Min, S., & Kim, B. (2024). AI Technology Adoption in Corporate IT Network Operations Based on the TOE Model. *Digital*, *4*(4), 947–970. https://doi.org/10.3390/digital4040047

Mittal, R. (2019). Transforming financial planning with AI-driven analysis: A review and perspective. *World Journal of Advanced Engineering Technology and Sciences*, *11*(1), 240–257.

Modiba, M. M., &Kekwaletswe, R. K. (2021). IT capability framework for digital transformation in South African financial service providers. *International Journal of Computer and Organization Trends*, *10*(2), 24–31. https://doi.org/10.2139/it-framework-financial-digitalisation

Mohammad, A., Al-Okaily, M., Al-Majali, M., & Masa'deh, R. (2022). Business Intelligence and Analytics (BIA) Usage in the Banking Industry Sector: An Application of the TOE Framework. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(4), 189. https://doi.org/10.3390/joitmc8040189

Moore, R., Seedat, Y., Chen, D. J. Y.-J., & Schoeman, W. (2021). *Artificial Intelligence—Is South Africa Ready*. https://repository.up.ac.za/bitstream/handle/2263/82719/Schoeman_Artificial.pdf?sequence=1andisAllowed=y

Msomi, L. (2024, March 15). *ITWeb TV: Absa prioritises AI for digital banking accessibility*. ITWeb. https://www.itweb.co.za/article/itweb-tv-absa-prioritises-ai-for-digital-banking-accessibility/raYAyMoreK67J38N

Mughal, R., Khan, A., & Hussain, T. (2022). Examining the role of human capital in AI adoption in financial institutions. *International Journal of Bank Marketing*, *40*(7), 1350–1375. https://doi.org/10.1108/ijbm-02-2022-0052

Nardi, P. M. (2018). *Doing survey research: A guide to quantitative methods* (4th.). Routledge.

Nel, J. H., & Boshoff, C. (2021). The influence of organisational climate and leadership on technology adoption in South African financial institutions. *Journal of Business Research*, *132*, 36–48. https://doi.org/10.1016/j.jbusres.2021.03.054

Nguyen, T. H., Le, X. C., & Vu, T. H. L. (2022). An Extended Technology-Organization-Environment (TOE) Framework for Online Retailing Utilization in Digital Transformation: Empirical Evidence from Vietnam. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(4), 200. https://doi.org/10.3390/joitmc8040200

Nieto-Rodriguez, A., & Vargas, R. V. (2023, February 2). How AI Will Transform Project Management. *Harvard Business Review*. https://hbr.org/2023/02/how-ai-will-transform-project-management

Norton Rose Fulbright. (2023). *The power of AI - How is artificial intelligence transforming financial services?* https://engage.nortonrosefulbright.com/33/32753/uploads/56336-glo-brochure--the-power-of-ai-edits-(update-to-55342)-v2.pdf?intIaContactId=loSWc%2fHWRID%2fnHJd%2fhz2pg%3d%3dandintExternalSystemId=1

Oates, B. J. (2006). *Researching information systems and computing*. SAGE Publications.

Odejide, A. O., & Edunjobi, T. E. (2024). AI in project management: Exploring theoretical models for decision-making and risk management. *Engineering Science and Technology Journal*, *5*(3), 1072–1085. https://doi.org/10.51594/estj.v5i3.959

Oliver Wyman. (2024). *Digitalization in financial services in South Africa*. https://www.oliverwyman.com/content/dam/oliver-wyman/v2/publications/2021/digitalization-in-financial-services-in-south-africa-updated.pdf

Oyekunle, D., Asante Darkwah, J., & Damilare Olusesi, L. (2024). Project Management Competencies in AI-Driven Environments: A Qualitative Assessment. *International Journal of Innovative Science and Research Technology (IJISRT)*, 1769–1779. https://doi.org/10.38124/ijisrt/IJISRT24APR1522

Pajares, J., & López, A. (2014). New Methodological Approaches to Project Portfolio Management: The Role of Interactions within Projects and Portfolios. *Procedia - Social and Behavioral Sciences*, *119*, 645–652. https://doi.org/10.1016/j.sbspro.2014.03.072

Pallant, J. (2020). *SPSS Survival Manual: A step by step guide to data analysis using IBM SPSS* (7th Ed.). Routledge. https://doi.org/10.4324/9781003117452

PMI. (2023). *Shaping the Future of Project Management With AI*. https://www.pmi.org/learning/thought-leadership/ai-impact/shaping-the-future-of-project-management-with-ai

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Pumplun, L., Tauchert, C., & Heidt, M. (2019). A new organizational chassis for artificial intelligence – Exploring organizational readiness factors. *Proceedings of the 27th European Conference on Information Systems (ECIS)*. https://aisel.aisnet.org/ecis2019_rp/163/

Rjab, A. B., Mellouli, S., & Corbett, J. (2023). Barriers to artificial intelligence adoption in smart cities: A systematic literature review and research agenda. *Government Information Quarterly*, *40*(3), 101814. https://doi.org/10.1016/j.giq.2023.101814

Salah, O. H., & Ayyash, M. M. (2024). E-commerce adoption by SMEs and its effect on marketing performance: An extended of TOE framework with ai integration, innovation culture, and customer tech-savviness. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(1), 100183. https://doi.org/10.1016/j.joitmc.2023.100183

SARB. (2020). *The SARB provides insight into disruptive innovation in financial services.* Fintech. https://www.resbank.co.za/en/home/quick-links/fintech

Schoeman, F., & Seymour, L. (2022). *Understanding the Low Adoption of AI in South African Medium Sized Organisations*. 257–243. https://doi.org/10.29007/c4rr

Schoeman, J., Seymour, L., & Roode, D. (2021). AI readiness in the South African financial services sector. *South African Journal of Information Management*, *23*(1), 1–9. https://doi.org/10.4102/sajim.v23i1.1357

Schumacker, R. E., & Lomax, R. G. (2004). *A beginner's guide to structural equation modeling, 2nd ed.* (pp. xii, 498). Lawrence Erlbaum Associates Publishers.

Silvius, G., & Marnewick, C. (2022). Interlinking Sustainability in Organizational Strategy, Project Portfolio Management and Project Management A Conceptual Framework. *Procedia Computer Science*, *196*, 938–947. https://doi.org/10.1016/j.procs.2021.12.095

Smith, R., Jones, T., & Daniels, M. (2023). Overcoming resistance to innovation in traditional industries: Insights from the financial sector. *Journal of Organisational Change Management*, *36*(5), 901–920. https://doi.org/10.1108/jocm-03-2023-0084

Solaimani, S., & Swaak, L. (2023). Critical Success Factors in a multi-stage adoption of Artificial Intelligence: A Necessary Condition Analysis. *Journal of Engineering and Technology Management*, *69*, 101760. https://doi.org/10.1016/j.jengtecman.2023.101760

Srinivasan, R., Diatha, K., & Singh, S. (2024). Adoption of cashless payment systems in the bottom-of-the-pyramid retail supply chains in India: A technology-organization-environment framework perspective. *Electronic Commerce Research*, 1–38. https://doi.org/10.1007/s10660-023-09803-4

Taherdoost, H. (2022). Validity and reliability of the research instrument; How to test the validation of a questionnaire/survey in a research. *International Journal of Academic Research in Management*, *11*(1), 28–36. https://doi.org/10.2139/ssrn.3205040

Taherdoost, H., & Madanchian, M. (2023). The impact of survey response rates on research validity and reliability. *Handbook of Research on Advanced Research Methodologies for a Digital Society*, 183–200. https://doi.org/10.4018/978-1-6684-6571-9.ch009

Taltrics. (2024). *Why AI is the future of resourcing for project portfolios: Enhancing your PPM with AI*. https://www.taltrics.com/resources/why-ai-is-the-future-of-resourcing-for-project-portfolios-enhancing-your-ppm-with-ai

Teller, J., Unger, B. N., Kock, A., & Gemünden, H. G. (2012). Formalization of project portfolio management: The moderating role of project portfolio complexity. *International Journal of Project Management*, *30*(5), 596–607. https://doi.org/10.1016/j.ijproman.2012.01.020

The Economist. (2022). *Banking on a game-changer: AI in financial services*. https://impact.economist.com/perspectives/sites/default/files/aiinfinancialservices.pdf

Toma, S. (2023). Organisational readiness and competitive pressures in big data adoption: Evidence from South Africa's banking sector. *International Journal of Business Innovation and Research*, *27*(3), 289–307. https://doi.org/10.1504/IJBIR.2023.10057515

Tornatzky, L. G., & Fleischer, M. (1990). *The Processes of Technological Innovation*. Lexington Books.

Tyson, J., & Sauers, N. J. (2021). Artificial intelligence adoption in K-12 education: Experiences of school leaders. *Journal of Educational Administration*, *59*(6), 655–673. https://doi.org/10.1108/jea-10-2020-0221

Van Selm, M., & Jankowski, N. W. (2006). Conducting online surveys. *Quality and Quantity*, *40*(3), 435–456. https://doi.org/10.1007/s11135-005-8081-8

Van Teijlingen, E., & Hundley, V. (2001). The importance of pilot studies. *Social Research Update*, *35*(1), 1–4.

Wang, S., Zhang, X., Peng, J., Tan, Y., & Fan, Z. (2024). Providing solutions for carbon emission reduction using the TOE framework. *Expert Systems with Applications*, *255*, 124547. https://doi.org/10.1016/j.eswa.2024.124547

Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change*, *201*, 123251. https://doi.org/10.1016/j.techfore.2024.123251

Zhang, L., Huang, Y., & Li, H. (2023). Fostering innovation through investment: The role of economic stability in AI adoption. *Journal of Business Research*, *148*, 24–38. https://doi.org/10.1016/j.jbusres.2023.03.001

Zhao, Y., & Wang, L. (2022). Organisational culture as a facilitator of AI adoption: A meta-analytical approach. *AI and Society*, *37*(3), 879–893. https://doi.org/10.1007/s00146-021-01186-7

Zulkipli, N. F. S., Sapry, H. R. M., Ahmad, A. R., & Nashrullah. (2024). Adoption of technology–organization–environment framework in the digitization decision of the inventory management. *Advances in Operations and Supply Chain Management Research (*, 102–114. https://doi.org/10.1007/978-3-031-55948-8_8

Appendix A: Participant Information Sheet

Good day,

My name is Kundishora Chisuro. I am completing my Master of Management degree in Digital Business at the University of the Witwatersrand, Johannesburg. I am researching **the adoption of AI for project portfolio management in South African financial services**.

As a key IT or project management decision-maker, you are invited to take part in this survey. The purpose of this study is to identify the factors that affect the adoption of AI for PPM in the financial services sector in South Africa.

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

The first part of the survey captures some demographic data. Please tick whichever boxes are applicable. The second part of the survey comprises 10 questions carrying 3 statements each. Please indicate the extent to which you agree with each statement, by ticking in the appropriate box. The entire survey should take between 5 to 10 minutes to complete. The survey was approved by the University Human Research Ethics Committee (Non-Medical), Protocol Number: WBS/DB2447481/221.

Thank you for considering participating. If you have any questions or wish to obtain a copy of the survey results, please contact me via e-mail or mobile number.

My contact details are: 2447481@students.wits.ac.za

My supervisor's details are as follows: Mr Mitchell Hughes (Mitchell.Hughes@wits.ac.za).

Kind regards,

Kundishora Chisuro

Master of Management Student: Digital Business

University of the Witwatersrand, Johannesburg

Appendix B: Research Instrument

	SECTION A: DEMOGRAPHIC DATA							
1	What is your age?	21-30	31-40	41-50	51-60	>60		
2	What is your level of education?	High school	Diploma	Bachelor	Post-graduate	Other		
3	What is your job title?							
4	What is your job level?	Top-Level Management	Middle-Level Management	First-Line Management	Specialist/Non-managerial			
5	How long have you been in your current role?	0-1 year	2-4 years	5-7 years	8-10 years	>10 years		
6	Are you involved in IT decision making in your business unit?	Yes	No					
7	Which of the following best describes your organisation?	Banking	Insurance	Advisory	Wealth management	Mutual funds	Financial services - Other	None of the above

	SECTION B: TECHNOLOGICAL FACTORS					
	Availability of AI Technologies (AAT)					
8	(AAT1) My organisation has sufficient access to state-of-the-art AI technologies.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
9	(AAT2) The necessary AI software is easily obtainable in my organisation.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
10	(AAT3) My organisation can easily acquire the AI technologies needed	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
	Technological Infrastructure (TIN)					
11	(TIN1) The technology infrastructure of my business unit can support AI-related technology.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree

12	(TIN2) The development of AI technology is compatible with my organisation’s legacy systems.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
13	(TIN3) My organisation's current IT systems can scale to support AI.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
	Data Quality (DAQ)					
14	(DAQ1) My organisation's data sources for AI applications are reliable.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
15	(DAQ2) The data available for AI in my organisation is accurate.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
16	(DAQ3) The data my organisation uses for AI is consistent across different sources.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
	SECTION C: ORGANISATIONAL FACTORS					
	Top Management Support (TMS)					
17	(TMS1) Top management in my organisation encourages innovation through AI.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
18	(TMS2) My top management allocates the necessary resources for AI adoption.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
19	(TMS3) My organisation’s top management is involved in strategic planning for AI adoption.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
	Skilled AI Technical Resources (STR)					
20	(STR1) My organisation has skilled technical staff for AI implementation.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
21	(STR2) My organisation provides adequate training for staff working on AI technologies.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
22	(STR3) My organisation can effectively recruit skilled AI professionals.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
	Organisational Culture (OGC)					
23	(OGC1) My organisation encourages innovation and experimentation with AI technologies.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree

24	(OGC2) Employees in my organisation are open to adopting new AI tools and technologies.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
25	(OGC3) Collaboration and knowledge sharing about AI are encouraged in my organisation.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
	SECTION D: ENVIRONMENTAL FACTORS					
	Government Regulation (GOR)					
26	(GOR1) South African government regulations support the adoption of AI.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
27	(GOR2) My organisation collaborates with regulatory bodies to ensure AI compliance.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
28	(GOR3) My organisation actively monitors changes in government regulations related to AI.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
	Market Competition (MAC)					
29	(MAC1) My organisation's AI strategies are shaped by competitive pressures.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
30	(MAC2) Competitors' use of AI drives my organisation to adopt similar technologies.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
31	(MAC3) My organisation invests in AI to respond to market competition.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
	Investment Conditions (INV)					
32	(INV1) My organisation benefits from a stable economic environment for AI investments.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
33	(INV2) My organisation has the financial resources needed for significant AI investments.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
34	(INV3) Supportive financial policies encourage my organisation to invest in AI.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
	SECTION E: ADOPTION FOR PPM (TOE COMBINED EFFECT)					
35	(CEF1) The interaction of technological, organisational, and environmental factors supports AI adoption for PPM in my organisation.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree

36	(CEF2) Combining technological, organisational, and environmental factors improves resource allocation for PPM in my organisation.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
37	(CEF3) Combining technological, organisational, and environmental factors improves efficiency and productivity for PPM in my organisation.	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree

Appendix C: Pilot Feedback

Respondent	Were the questions easy to understand? If any were unclear, please specify which ones.	Was the length of the survey appropriate? Please specify whether it felt too long or too short and how much time it took you to complete.	Do you think any important questions were missing? If so, please list them.
1	The questions relating to combining factors improving resource allocation, efficiency and productivity were a bit unclear. Maybe specifying what specific factors are being referred to or providing an example might help. On the question on how many years are you in your current role, maybe some guidance on whether it should be rounded up or down would help (e.g., 1 year and 3 months, should be submitted as 1 year).	The length was appropriate.	A suggestion is to provide a high-level definition or description of what AI technologies refer to within the context of the survey (at the beginning of the survey). This would give everyone the same context for answering the questions.

2	They were easy to understand, but my level of knowledge towards them was not great. AI is encouraged but it is not as widely used as it should be as yet	Yes, it was.	Safety of AI. Nothing really covered the security of it much.
3	Yes, but I had no experience in the area under question. Not sure if you want to do purposive sampling to collect more meaningful data.	Felt fine, took 5min	Maybe adding "I do not know" to the Likert scale if you are not going to have any sampling screening
4	The questions required one to pause and think of what the organisations is approach and readiness to AI. The last 3 required advanced thinking if one is not up to date with AI market developments.	It was ok. A suggestion to add a page count or progress indicator so one knows how many more pages to go etc.	Qualifying questions. I was unclear on this.

Appendix D: Summary of Pilot Survey Changes

Item	Pre-pilot	Post-pilot	Changes made
Whole Survey	No progress bar.	A progress bar was visible for each page.	Included a completion progress bar on each page.
Q4 - What is your job level?	The question did not exist.	What is your job level? • Top-Level Management • Middle-Level Management • First-Line Management • Specialist/Non-managerial	Added a new question with drop-down options: What is your job level?
Q7 - Which of the following best describes your organisation?	Banking Insurance Advisory Wealth management Mutual funds Financial services - Other	Banking Insurance Advisory Wealth management Mutual funds Financial services - Other None of the above	Added a seventh option stating: "None of the above".
Q8 - Availability of AI Technologies	Availability of AI Technologies.	Availability of AI Technologies (e.g., Machine Learning, Deep Learning, Generative AI)	Added AI technologies to refer to: "e.g. Machine Learning, Deep Learning, Generative AI".
Q17 - Interaction of TOE Factors	Interaction of TOE Factors	Interaction of Technology, Organisational and Environmental Factors (discussed in the previous questions above)	1. Expanded TOE to say "Technology, Organisational and Environmental" 2. Appended the following phrasing at the end: "(discussed in the previous questions above)".

Appendix E: Ethics Clearance Certificate

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/DB2447481/221

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

Project title	The adoption of AI for project portfolio management in South African financial services
Investigator / Researcher	Mr Kundishora Chisuro
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonyr and confidentiality.
Issue Date of Certificate	02/09/2024
Expiry date	Date of submission of the project / research report
Chairperson	Dr Ayanda Magida ☎ +27 11 717 3953 ayanda.magida@wits.ac.za

Declaration by Researcher

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

I fully understand the conditions under which I am authorized to carry out the abovementioned research an 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

06-Sep-2024
Date:

Appendix F: Turnitin Report

The adoption of AI for project portfolio management in South African financial services-2.pdf

ORIGINALITY REPORT

4%	4%	4%	%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	wiredspace.wits.ac.za Internet Source	2%
2	Adewale Samuel Hassan. "Factors Driving Artificial Intelligence Adoption in South Africa's Financial Services Sector", Academic Journal of Interdisciplinary Studies, 2024 Publication	1%
3	Koshanam, Venkat Ramanathan. "Facilitating Ethical Adoption of Artificial Intelligence Technologies in the Public Sector", University of Maryland University College, 2024 Publication	1%

Exclude quotes	On	Exclude matches	< 1%
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