The adoption of artificial intelligence in financial services in South Africa

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DECLARATION

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

Name: Anele Qwabaza Signature:

Signed at Samrand

On the 25 day of Feb 2022

DEDICATION

This paper is dedicated to my late father, Vuyisile Lucas Qwabaza, who continuously encouraged me to further my studies and has supported me in every way. His love and belief in me remain my most treasured memories.

This paper is also dedicated to my wife, Nosihle Anesipho Qwabaza, whose love, patience and support have carried me throughout my master's journey, and to my son Luminathi Qwabaza who always brings a smile to my face.

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ABSTRACT

Artificial intelligence (AI) is one of the driving forces behind disruptive innovations and has transformed how organisations interact and deliver services to their customers. While factors that enable the successful implementation of AI in organisations were previously studied, these studies are still in the early stages. Therefore, the objective of this study was to investigate the success factors for AI adoption by South African financial services companies, using an integration of the diffusion of innovation (DOI) theory and the technology-organisation-environment (TOE) framework. This study also aimed to understand the relative effect of factors affecting AI adoption in financial services in South Africa.

The study was administered using an online survey targeting employees of South African financial services organisations. Structural equation modelling (SEM) was used to analyse the data. The results show that only complexity and technical capabilities significantly influenced AI adoption, with managerial capabilities indirectly influencing the adoption of AI in South African financial services. Therefore, when adopting AI in their organisations, the leadership of financial services organisations should consider the costs associated with AI applications, the time taken to innovate using AI, and the application of AI. External environmental factors, government involvement, competitive pressure, and vendor partnerships all had statistically significant results for AI adoption.

In addition, this study also aimed to understand the assimilation of AI by customers after adoption by organisations, using the technology acceptance model (TAM). The data was collected using an online survey targeting external customers of financial services organisations, and it was analysed using SEM. The results show that perceived ease of use and perceived usefulness are important indicators of how customers experience AI applications of financial services organisations. Therefore, financial services organisations should ensure an optimal level of ease of use and prioritise utilitarian benefits when designing and adopting AI applications.

Keywords: Artificial intelligence, DOI, financial services, TAM, TOE, user experience

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LIST OF ACRONYMS

Acronym	Description
4IR	Fourth industrial revolution
AI	Artificial intelligence
DOI	Diffusion of innovation
EDA	Exploratory data analysis
IS	Information system
IT	Information technology
KYC	Know your customer
ML	Machine learning
NLP	Natural language processing
PEOU	Perceived ease of use
PU	Perceived usefulness
SEM	Structural equation modelling
TAM	Technology acceptance model
TOE	Technology-organisation-environment
TPB	Theory of planned behaviour
TRA	Theory of reasoned action

CHAPTER 1. INTRODUCTION

1.1 Purpose of the study

The purpose of this study is to understand the success factors for artificial intelligence (AI) adoption by South African financial services companies by leveraging existing studies in the adoption of AI by organisations (Chen, 2019; Mariemuthu, 2019; Rao, 2017) and past studies in the adoption of emerging technologies.

1.2 Context of the study

Artificial Intelligence (AI) is one of the driving forces behind the fourth industrial revolution (4IR) and a key enabler for disruptive innovation that leads to game-changing products and services and improved customer experience (Khamis, 2019). AI can transform the way financial services deliver services to their customers. Financial services can use AI to streamline processes, offer personalised products, and improve customer experience and financial advisory services.

However, in South Africa, AI and other emerging technologies have yet to be adopted with any enthusiasm by South African enterprises (Goldstuck, 2019). A study conducted by World Wide Worx in partnership with Syspro, a South African software development company, reveals that only 13% of corporates in South Africa are currently using AI, and, of the rest, 21% plan to adopt it in the next 12 to 24 months (Goldstuck, 2019). Oliveira et al. (2014) cited the risks associated with adopting emerging technologies as one of the reasons for slow adoption. Therefore, like any emerging technology, businesses seeking to adopt AI must apply due diligence to ensure that the right solution is adopted, in line with the business strategy.

A review of academic literature for impact studies on the adoption of AI by organisations identified limited literature in this area. According to AlSheibani et al. (2018), most of the literature relates to AI techniques and applications, with a narrow focus on adoption by organisations.

1.3 Research problem

The use of AI tools has recently increased across all industries and sectors, driven by the increase in digital data and computational capacity (Fernández, 2019). Financial institutions can now analyse high volumes of data faster to understand their customers better and offer personalised services.

Chen (2019) researched the success factors impacting AI adoption by organisations but only focused on telecoms companies in China. More studies covering other industries and countries still need to be conducted to get a general and holistic understanding of factors influencing AI adoption in organisations.

Within the South African context, studies by Rao (2017) and Mariemuthu (2019) also investigated factors that influence the adoption of AI by South African organisations. In his research, Rao (2017) examined factors critical to the adoption of AI by South African organisations through a qualitative study by using a combination of diffusion of innovation (DOI), institutional theory and technology-organisation-environment (TOE) frameworks and suggests testing the validity of this framework through a different study. Mariemuthu (2019) used the TOE framework to investigate factors influencing AI adoption by South African banks and suggests that a different theoretical framework be used to investigate factors influencing the adoption of AI as the TOE framework does not provide a definitive model. Accordingly, this research aims to understand the success factors for AI adoption by South African financial services companies.

A study by Capgemini (2018) shows that while organisations have made great strides in gaining customers' trust in AI interactions, the organisations struggle to increase customer satisfaction from such interactions. According to the study, customers will consider an AI experience to be positive if it provides a unique experience beyond their expectations. Therefore, this research also aims to understand the assimilation of AI by customers after adoption by organisations.

This research proposes and tests a framework for AI adoption by combining the DOI and TOE frameworks and examining them within the South African context. The framework consists of technological factors, environmental factors, organisational factors, and innovation attributes of AI. This research also uses the TAM framework to analyse the customer experience from AI-enabled services or AI applications after adoption by financial services organisations.

1.4 Research objectives

This study aims to investigate success factors for AI adoption by South African financial services companies.

In line with the purpose, this study seeks to achieve the following objectives:

1. Understand the factors that influence the adoption of AI technologies in financial services in South Africa
2. Understand the relative effect of each of these factors in affecting AI adoption in financial services in South Africa

3. Understand customer experience of AI applications after adoption by financial institutions

1.5 Significance of the study

Artificial intelligence influences many aspects of human lives, with organisations across various industries trying to figure out ways of using AI to their advantage. As business leaders and innovators race to achieve AI's promise of competitive advantage, the technology alters industries from finance to manufacturing with new products, processes, and capabilities (Marr, 2018). Since AI is still an emerging technology, business leaders looking to adopt AI face risks of being early adopters; therefore, developing a framework to assist business leaders in decision-making capability in adopting AI is critical (Rao, 2017). The framework proposed in this research will help business leaders make decisions about AI adoption.

Existing literature on AI adoption by organisations is still in the infancy stages. The majority of existing literature on AI mainly focuses on techniques and applications (AlSheibani et al., 2018). This research will contribute to the body of literature on impact studies on the adoption of AI as an emerging technology by an organisation. In addition, this study will help organisations understand factors that must be considered when adopting AI.

AI technology changes the way companies interact with their customers and potentially improves the companies' relationships with their customers. More specifically, AI advancements can improve the customer experience by allowing businesses to learn more about customers' preferences and purchasing behaviour (Evans & Ghafourifar, 2019). The strategic use of AI technologies at various key points of contact with clients can therefore bring significant benefits to businesses and the possibility of increasing customer satisfaction (Ameen et al., 2021). As such, this research aims to help managers understand the impact of their decision to adopt AI in their organisations on customer experience.

1.6 Delimitations of the study

I. The scope of the research is limited to the adoption of AI by South African financial services companies.

II. The scope of enquiry is limited at an organisational-level study and thus focuses on factors that influence AI adoption at an organisational level rather than individuals working for financial services.

1.7 Definition of terms

Financial services sector	The financial services sector comprises all authorised financial service providers: banks, insurance companies, asset management companies, and stock exchange (Investopedia, 2021).
Artificial intelligence	Artificial intelligence (AI) is a branch of computer science that deals with the development of computer programmes to perform tasks that would otherwise require human intelligence (Chen, 2019).
Machine vision	Machine vision is a subfield of AI that train computers to see and perceive their surroundings (SAS, 2021).

Expert systems	Expert systems are computer applications developed to solve complex problems using information and reasoning techniques usually associated with a human expert.
Natural language processing	Natural language processing (NLP) is a subset of artificial intelligence that deals with the interaction between computers and humans using natural language (Garbade, 2018).
Machine learning	Machine learning (ML) is an application of AI that uses algorithms and neural network models to learn automatically from specific training data without being explicitly programmed.
Customer experience	Customer experience is what the customer feels over time while interacting with an organisation's products and services through its various channels.

1.8 Assumptions

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

- Respondents reflect normal perspectives and experiences to ensure that the study reflects the true nature of the experience.
- The sample is representative of the South African financial services population.

1.9 Chapter outline

The subsequent chapters of this study include a thorough review of the literature and the research methodology adopted for this study.

Chapter 2: Provides a literature review of AI adoption and customer experience and outlines a history of AI and theoretical foundations for its adoption. Two research models are proposed based on 1) an integrated framework of diffusion of innovation (DOI) (Rogers, 2003) and technology-organisation-environment (TOE) (Tornatzky & Fleischer, 1990) to investigate the factors that influence AI adoption, 2) technology acceptance model (TAM) model to analyse customer experience after the adoption of AI by organisations. The research models are followed by the research method and proposed hypotheses.

Chapter 3: Outlines the research instruments and the data collection procedure to address the research objectives of the study.

Chapter 4: Presents the results of the identification of factors that influence the adoption of AI by South African financial services organisations and how customers experience AI-enabled products and services after adoption by financial services organisations.

Chapter 5: Presents an in-depth analytical discussion of the data analysis results presented in Chapter 4, including the demographic profiles of respondents and an in-depth discussion of results pertaining to hypotheses testing.

Chapter 6: Discusses the conclusions of both the AI-adoption study and the customer experience study, makes recommendations to South African financial services organisations, and proposes areas for future research.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

This chapter reviews previous research on technology adoption models and builds an argument for their applicability in the adoption of AI by South African financial services firms. The chapter defines and outlines AI evolution and looks at AI technologies and applications. A review of literature on technology adoption models and assimilation of technology to customers is provided, followed by a theoretical framework for AI adoption and customer experience after the adoption of AI technologies by organisations.

2.2 Artificial intelligence

2.2.1 History of AI

Artificial intelligence (AI) is seen as the transformational technology of the digital age and the electricity of this century that will power everything (Chan-Olmsted, 2019). The emergence of artificial intelligence officially dates to a 1956 conference at Dartmouth College (Mijwil, 2015). At the time, researchers gathered to develop concepts around 'thinking machines' and laid down the framework for academic exploration. High-level computer languages such as FORTRAN, LIPS, and COBOL were invented to teach machines to perform sophisticated tasks such as playing chess, proving mathematical models, and identifying objects, people, and languages.

Later, AI definitions evolved to focus on intelligent machines. For example, Winston (1992) defines AI as the study of the computations that enable perception, reasoning, and action. Nilsson (2010) defined AI as an activity devoted to making machines intelligent. Nowadays, modern dictionary definitions focus on AI as a branch of computer science and how machines can mimic human intelligence (Marr, 2018). Figure 1 shows the chronology of the development of AI.

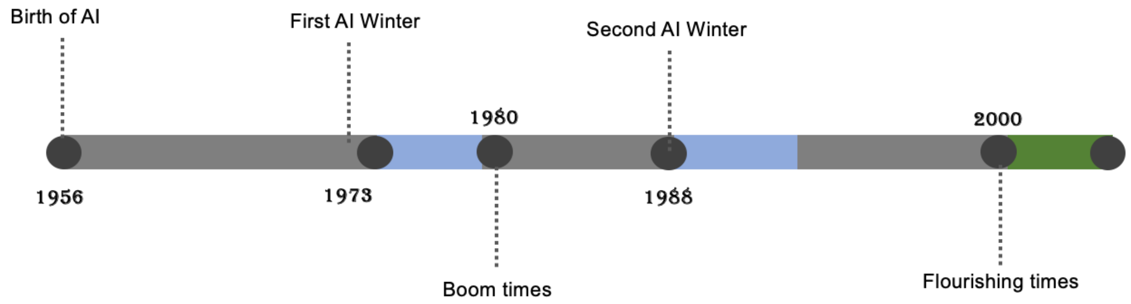

Figure 1: Timeline of early AI developments (Schuchmann, 2019a)

Between 1957 and 1974, early demonstrations of AI such as the General Problem Solver (GPS), developed by Allen Newell and Herbert Simon, and the early natural language processing computer programme, ELIZA, developed by Joseph Weizenbaum, showed promising results towards problem-solving and spoken language interpretation (Anyoha, 2017). These early successes increased optimism and expectations of AI, leading to increased AI research funding by agencies such as the United States Department of Defence. However, computers lacked the capacity to process information fast enough to produce meaningful outcomes, leading to reduced AI funding.

From 1973, funding into AI research dried out as promises of AI failed to materialise, marking the first winter of AI. A report by James Lighthill criticised the state of AI research and is viewed as a significant contributor to slowing down funding into AI research (Agar, 2020).

In the 1980s, the introduction of expert systems that mimicked human experts' decision-making process (Anyoha, 2017) reignited interest and funding of AI research. The Japanese government invested in the Fifth Generation Computer Project to create new computer technology and improve computational power (Feigenbaum & Shrobe, 1993).

AI experienced another significant winter from 1987 to 1993 as the expert systems central to the revolution faced many issues. Researchers feared that AI might not deliver the expected results yet again, leading to a decline in general interest in AI (Schuchmann, 2019b).

In the 1990s, with advances in computing power, there was renewed funding and interest in AI. In 1995, Richard Wallace developed ALICE, a chatbot that could hold a basic conversation (OECD, 2021). In 1997, IBM developed Deep Blue, a chess-playing computer that could win chess games against reigning world chess champions (Campbell et al., 2002). After 2000, AI continued to grow with more AI applications being created.

2.2.2 Technology and application of AI

AI is not a single technology but a set of software and programmes for integrating with numerous applications. These AI applications are classified according to how the machines' cognitive abilities compare to human intelligence (Zhu et al., 2020). AI applications have increased considerably in recent times across financial services and other sectors.

2.2.2.1 Machine vision

Machine vision refers to technology in which computers digitise images, process the data, and perform various actions (Calderone, 2019). The first commercial use of machine vision was to interpret typed or handwritten text using optical character recognition. This advancement was used to interpret written text for the blind (Thompson, 2021). Today, machine vision is widely used in video surveillance, self-driving cars, health care, material inspection, object and facial recognition, pattern recognition, signature, optical character, and currency recognition.

2.2.2.2 Expert systems

Expert systems are among the earliest branches of AI commercialised, producing a series of resounding successes in the early and mid-1980s (Gill, 1995). Expert systems are computer programmes that solve problems using a series of rules in 'if-then' statements. These statements or rules are applied to a knowledge base containing previous experience about a particular scenario. Expert systems were applied in various industries, including financial services.

2.2.2.3 Natural language processing (NLP)

Natural language processing (NLP) is an area of research and application that explores how computers can be used to understand and manipulate natural language text or speech to do useful things (Chowdhury, 2003). NLP research has benefited significantly from the introduction of machine learning algorithms for language processing and transfer learning, enabling the reuse of pre-trained models on new problems. Application of NLP includes machine translation, natural text processing and summarisation, multilingual and cross-language information retrieval, and speech recognition (Chowdhury, 2003).

2.2.2.4 Machine learning

Machine learning (ML) is the use of algorithms to automatically learn patterns from specific training data, which can be used to predict future patterns. The development of machine learning dates to the late 1940s and has evolved as more data and computing power became available. Today, progress in ML allows the rise of intelligent systems with cognitive capabilities (Janiesch et al., 2021), such as Siri and Alexa, and allows businesses to improve their decision-making and better service their customers. Other applications of ML include fraud detection, self-driving cars, medical diagnoses, product recommendations, stock market trading, and virtual assistants.

2.2.3 Applications of AI in financial services

The use of AI in the financial sector started with the release in 1900 of *Theory of Speculation* by Louis Bachelier. Bachelier explored the use of mathematics to evaluate stocks (Swaine-Simon, 2018). Recently, AI gained popularity driven by the growing volume of digital data available, increased data storage and computational processing capacity and lower cost, and the progress made in the algorithms used (Fernández, 2019).

Using AI tools, financial institutions can process larger amounts of data faster to provide personalised customer services, speed up credit decisions, and enable fraud and risk management decisions. For example, Wells Fargo announced that its 13 000 ATMs would work without debit cards (Forbes, 2019), and Standard Bank uses facial recognition on their app security to create a safe and secure banking experience for their customers (Mzekandaba, 2020). In addition, advancements in AI algorithms enable more precise results, increasing the reliability of AI applications. For example, Banco Bilbao Vizcaya Argentaria (BBVA) bank uses machine vision for know your customer (KYC) verification (Forbes, 2019). Figure 2 show various areas of financial services where AI is applied:

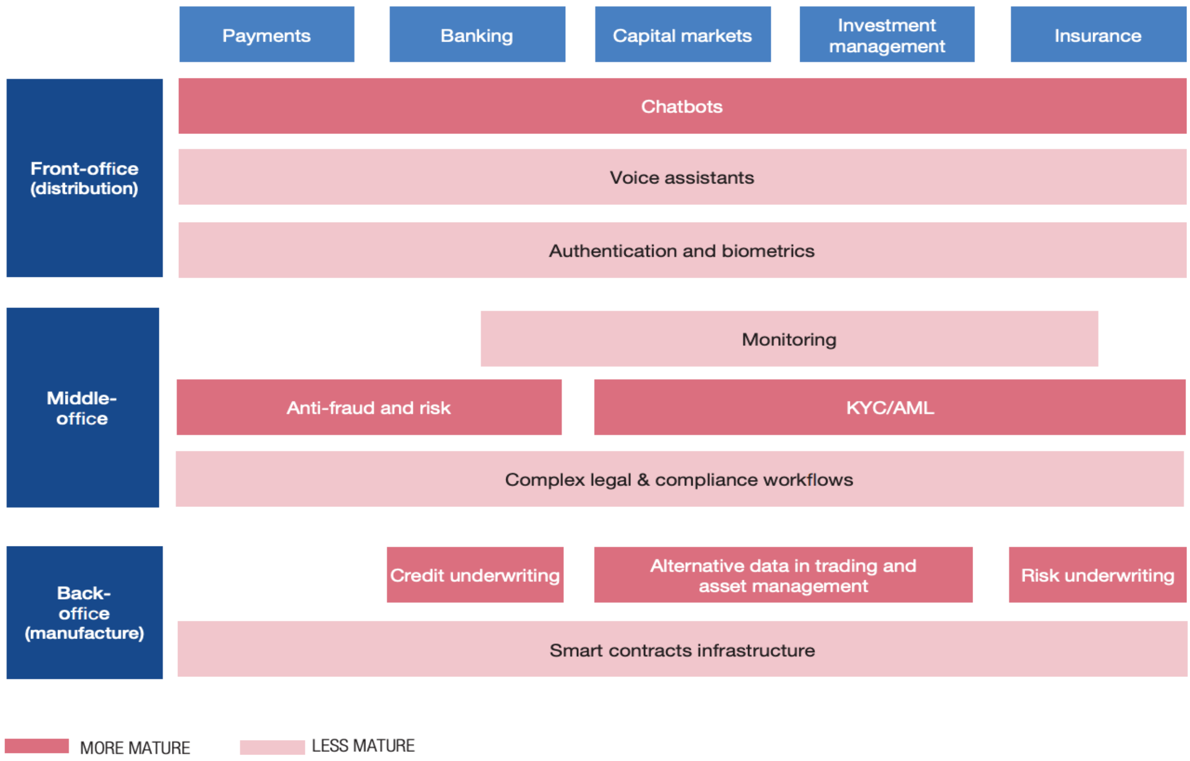

Figure 2: Applications of AI in financial services (Fernández, 2019)

2.3 Theory base for AI adoption

2.3.1 Information technology adoption

Today, information technology (IT) plays a significant role in enabling business strategies. Therefore, organisations adopt IT innovations to improve their competitiveness and decision-making, and to enhance the customers' experiences. As such, this research seeks to leverage existing theoretical models for IT adoption to understand the drivers of IT innovation adoption of South African financial services.

Technology adoption models were widely researched both at an individual and organisational level. At an individual level, the theory of reasoned action (TRA) by

Fishbein and Ajzen (1975) is amongst the first models to be developed. TRA states that people's behaviour is influenced by their attitudes, intentions, and social norms. According to TRA, external factors influence behaviour and indirectly influence attitude. Ajzen (1991) improves TRA by including a third factor, namely perceived behavioural control, to form the theory of planned behaviour (TPB). However, TRA and TPB lacked user intentions concerning the acceptance of technology (Cruz et al., 2010). Davis (1985) technology acceptance model (TAM) addressed the shortcoming of the TRA and TPB models. TAM considers additional factors to TPB, including perceived usefulness and perceived ease of use (Cruz et al., 2010). TAM is a valuable tool for predicting customer satisfaction, improving customer service, and enhancing service quality (Rod et al., 2009). According to Rod et al. (2009), ease of use and usefulness are essential factors when evaluating online service quality. Accordingly, this study uses these two factors to understand customer experience after AI adoption by firms.

Other adoption models at the individual level include technology acceptance model 2 (TAM 2) developed by Venkatesh and Davis (2000) and the unified theory of acceptance and use of technology (UTAUT) by Venkatesh et al. (2003). TAM 2 extends TAM by incorporating two processes: social influence and cognitive instrumental processes. In contrast, UTAUT (Venkatesh et al., 2003) extends TAM 2 to predict the users' behavioural intentions to adopt technology and use technology (Chen, 2019).

At the organisational level, the technology-organisation-environment (TOE) framework developed by Tornatzky and Fleischer (1990) is a valuable to measure technology adoption decisions. TOE identifies technological context, organisational context, and environmental context as key aspects influencing an organisation to adopt and implement a technological innovation. Another instrumental model is the diffusion on innovation (DOI) theory developed by (Rogers, 1995). While there are other models such as the institutional theory (Scott & Christensen, 1995), this research only considers the DOI, TOE, and TAM frameworks to measure factors influencing adoption decisions by organisations and customer experience from AI-enabled services and applications after adoption by organisations.

2.3.2 Diffusion of innovation (DOI)

The diffusion of innovation (DOI) refers to the process that occurs as people adopt a new idea, product, practice, philosophy, among others (Kaminski, 2011). Rogers divides technology adopters into five categories: innovators (people who want to be the first to try an innovation), early adopters (people who are opinion leaders), early majority (people who need to see evidence that the innovation works before they are willing to adopt it), late majority (people who are sceptical of change and will not adopt an innovation until the majority has tried it), and laggards (very late adopters who make decisions conservatively with regards to technology) (Kaminski, 2011; Rogers, 1995). The adoption of an innovation is influenced by five main factors: relative advantage, complexity, compatibility, observability, and trialability (Chen, 2019; Kaminski, 2011; Oliveira & Martins, 2011; Rogers, 1995). These factors affect the five adopter categories to varying degrees. However, of these five factors, only three enjoy prevalence in extant empirical studies, namely relative advantage, compatibility, and complexity (Beatty et al., 2001; Chong et al., 2009; Nilashi et al., 2016). Therefore, this research only considers these three factors.

The innovation process at the organisational level is complex (Kaminski, 2011), and is represented in Figure 2. Three factors affect the innovation process, namely individual characteristics (leader attitude towards change); internal organisational structural characteristics (centralisation, complexity, interconnectedness, the number of employees, and organisational slack); and external characteristics of the organisation (system openness) (Isma'ili & Zahir, 2017; Oliveira & Martins, 2011; Rogers, 1995). DOI emphasises that both the individual and organisational factors influence the innovativeness of an organisation.

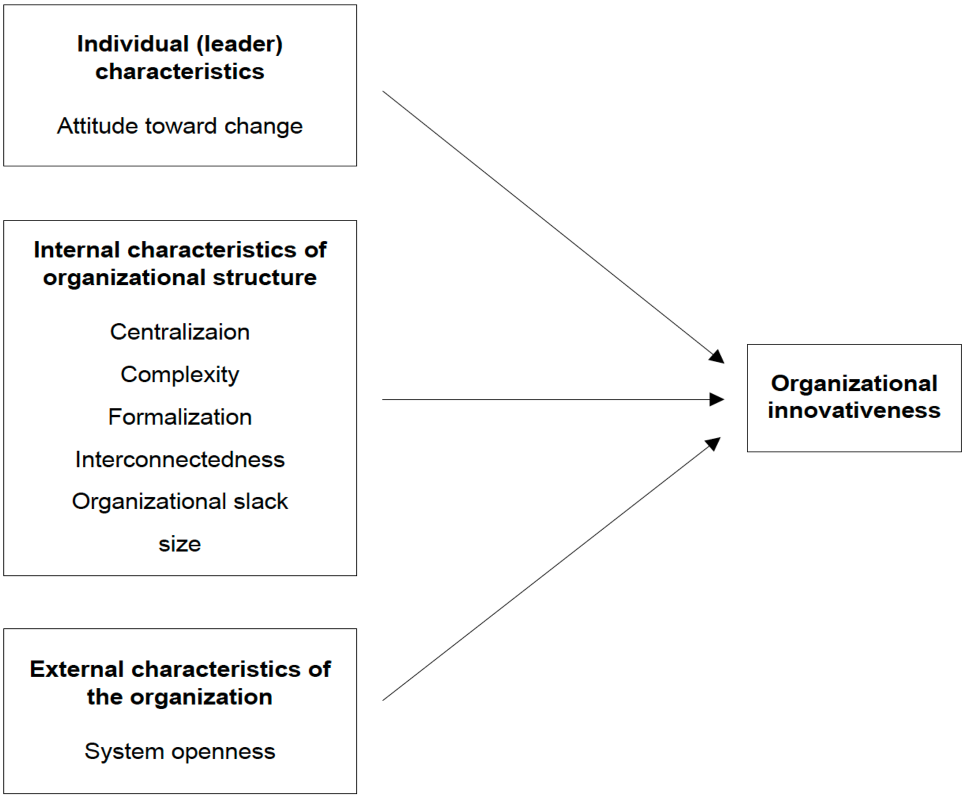

Figure 3: Innovation process at the organisational level (Rogers, 1995)

Definition of each of the organisational characteristics (Rao, 2017; Rogers, 2003):

i. Centralisation: Power and decision-making are delegated to a few individuals within an organisation.

ii. Complexity: The depth of skills and competencies in an organisation
iii. Formalisation: Emphasis on employees to follow the rules and procedures
iv. Interconnectedness: The extent to which interpersonal networks enable information flow within an organisation.
v. Organisational slack: The extent to which excess capacity is maintained in an organisation
vi. Size: Size of the workforce in an organisation

2.3.3 Technology-organisation-environment (TOE)

The technology-organisation-environment (TOE) framework identifies three aspects of an organisation that influence how an organisation adopts and implements a technological innovation in three contexts: technological, organisational, and environmental (Chen, 2019; Chen et al., 2021). Technological context includes new and existing technologies within an organisation. These technologies become a benchmark when new technology is adopted. Factors such as ease of use, perceived benefits and usefulness, complexity of integration, and IT infrastructure are usually considered relevant factors influencing the IT adoption process (Chen, 2019; Kuan & Chau, 2001; Mariemuthu, 2019; Oliveira & Martins, 2011).

This includes skills and expertise, strategies and policies, number of employees and size of excess capacity within the organisation (Mariemuthu, 2019; Mudzana & Kotze, 2015; Rao, 2017; Yang et al., 2013). Previous research found that top management support is key in the technology adoption process (Low et al., 2011; Shoniwa, 2016). Senior managers are key in establishing an innovation and learning culture in an organisation and encouraging the organisation to experiment and adopt new technology to support and deliver the organisation's vision and strategy.

The environmental context refers to the area in which organisations do business, including industry structure, the presence or absence of technology service providers, and the regulatory environment (Baker, 2012; Dwivedi et al., 2011). Industry structure includes the competitiveness of the firm's environment, including the ease with which new players can enter that market. Intense competition stimulates innovations in the market. Also, a dominant player in a particular market can influence other organisations to innovate (AlSheibani et al., 2018). The high presence of technology service providers can positively impact the costs associated with technology adoption and accelerate the adoption of technology by organisations. The regulatory environment also plays an important role in the innovativeness of the industry. Stringent safety and testing requirements can reduce the in-industry rate of innovation (Baker, 2012). Other environmental drivers include market uncertainty (Teo et al., 2006), industry pressure (Kuan & Chau, 2001), and regulatory policy (Pan & Jang, 2008).

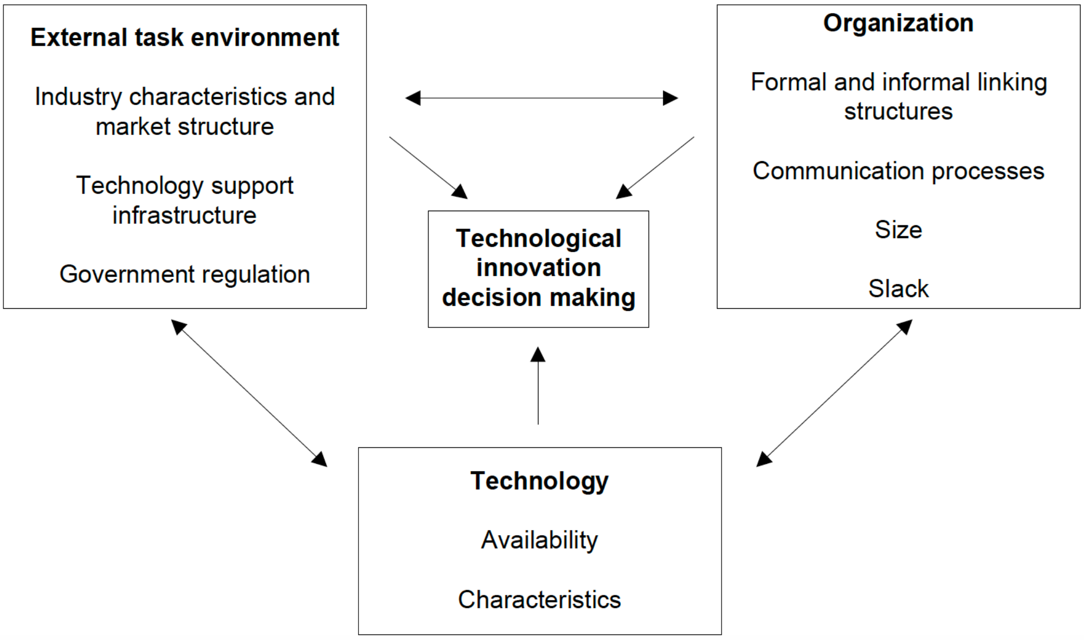

Figure 4: Technology, organisation, and environment framework (Tornatzky & Fleischer, 1990)

Therefore, the TOE framework has proven to be a useful theory for studying IT innovations at the organisation level and was validated through several studies (Chen et al., 2021; Yang et al., 2013). As such, this study leverages constructs used in previous studies and tests them in the context of organisational adoption of AI for each of the three TOE contexts: technological, organisational, and environmental.

2.3.4 Technology acceptance model (TAM)

The technology acceptance model (TAM) was developed by Davis (1989) to address the shortcomings of the TRA and TPB models by including two additional factors, namely perceived usefulness and perceived ease of use (Davis et al., 1989). Perceived usefulness is defined as the extent to which a person believes that using a particular system would improve their job performance and ease of use and the extent to which they believe that using a particular system would be free of effort (Dwivedi et al., 2011). TAM is continuously researched and expanded (Isaac et al., 2018; Rod et al., 2009; Venkatesh & Davis, 2000; Venkatesh et al., 2003). In a study by Isaac et al. (2018) to predict internet use by employees in organisations, the researchers proposed an extension to TAM to incorporate two additional factors: user satisfaction and performance impact. The study examined the impact of perceived ease of use and perceived usefulness on user satisfaction. The results show that perceived ease of use and perceived usefulness positively impact user satisfaction (Isaac et al., 2018). Therefore, this study uses perceived ease of use and perceived usefulness, and includes user satisfaction to investigate customer experience regarding AI-enabled services and applications after AI adoption by South African financial services.

2.4 Proposed theoretical framework and hypotheses

AI adoption

The literature review shows limited knowledge at an organisational level of enabling factors for AI adoption and how these factors inter-relate to influence the decision to adopt. This study proposes an integrated framework of DOI and TOE to investigate factors influencing AI adoption by South African financial services organisations. The proposed framework categorises the AI adoption factors into innovation attributes, organisation capability, and external environment, as outlined in Figure 5.

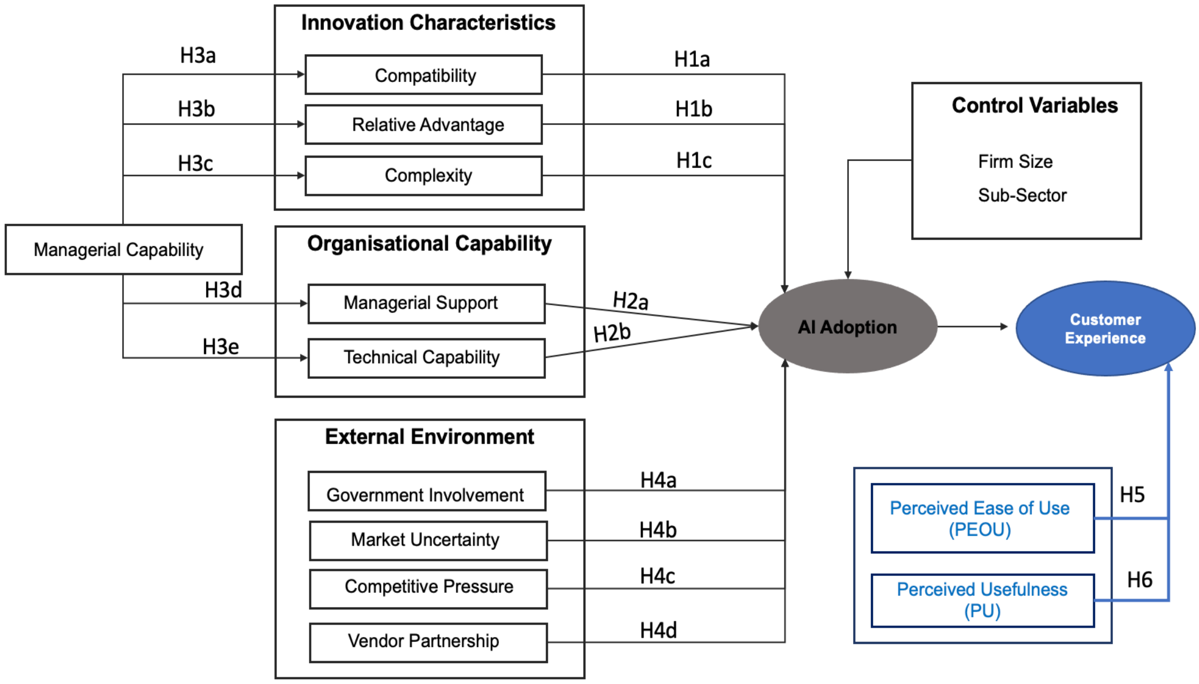

Figure 5: A research framework for AI adoption at the firm level (adapted from Chen (2019))

Innovation attributes of AI

Rogers (1995) suggests that adopting innovation is influenced by five main factors: relative advantage, complexity, compatibility, observability, and trialability (Al Rahbi, 2017; Rogers, 1995). Among these five factors, only relative advantage, complexity, and compatibility have enjoyed prevalence in past studies (Beatty et al., 2001; Chen, 2019; Chen et al., 2021; Oliveira et al., 2014) were therefore considered in the proposed framework.

Compatibility

Compatibility relates to the scope of innovation and how it is able to provide a valuable experience to the intended user while also meeting their needs (AlSheibani et al., 2018; Rogers, 1995). According to Chan (2019), when innovation is compatible with the experience and requirements, it leads to higher adoption. Positive relation is validated by previous studies on innovation (Chen, 2019; Ifinedo, 2005; Zhai, 2010). A positive relation between innovation compatibility and innovation adoption leads to the following hypothesis:

H1a. *There is a positive relationship between compatibility and AI adoption.*

Relative advantage

Relative advantage refers to the perceived benefits of adopting innovation (AlSheibani et al., 2018) or the extent to which an innovation is seen as better than the idea, programme, or product it replaces (Chen et al., 2021). The perceived benefit of an innovation significantly affects an organisation's intention to adopt innovative technology (AlSheibani et al., 2018; Chen, 2019). The perceived benefit of the innovation was validated by other studies on the adoption of innovation (Chen, 2019; Ifinedo, 2005). Using AI tools, financial institutions can provide personalised value-adding services to their customer, reduce costs, and improve operational efficiency. Therefore, relative advantage leads to the following hypothesis:

H1b. *There is a positive relationship between relative advantage and AI adoption.*

Complexity

Complexity is the degree to which innovation is considered relatively difficult to understand and use (Chen, 2019). The easier it is to integrate technology into business activities, the greater the likelihood of adoption (Rao, 2017). Particularly in the South African context, the complexities of AI lie in its immaturity, limited programming and data skills in the market, perceived difficulty, and cost of developing AI applications. When the technology matures, organisations understand the complexity and risks associated with adoption and how to derive business value from that technology. Perceived complexity leads to the following hypothesis:

H1c. *There is a negative relationship between complexity and AI adoption.*

Organisational capability

Managerial support

Top management support refers to senior leadership's commitment to IT implementation (Ifinedo, 2005), and it is an essential factor in the adoption and implementation of new technology (Mariemuthu, 2019). AI technologies can bring organisation-wide changes. In South Africa, AI-powered technologies such as robotic process automation (RPA) significantly impact job losses when financial institutions automate processes to boost service delivery. These AI applications require management support for acquisition and adoption. The need for management support leads to the following hypothesis:

H2a. *There is a positive relationship between managerial support and AI adoption.*

Technical capability

Technology capabilities refer to tangible and intangible assets essential to adopt innovation, such as IT strategies and policies, IT infrastructure, and data (Mariemuthu, 2019). Strong technical capabilities reduce integration complexity and enable IT divisions to deploy AI technologies quickly and efficiently (Chen, 2019). In turn, technical capabilities drive the adoption of AI applications in the organisation. Therefore, the need for technical capability leads to the following hypothesis:

H2b. *There is a positive relationship between technical capabilities and AI adoption.*

Managerial capability

Managerial capability refers to the leadership capability of an organisation. Managers are key in establishing an innovation and learning culture in an organisation and encouraging the organisation to experiment and adopt new technology to support and deliver the organisation's vision and strategy. While it may be relatively easy for an organisation to invest in new technology, changing the culture by adopting new technology is much more difficult and requires deliberate actions. This requirement for management capability for establishing a technology-adopting culture leads to the following hypotheses:

H3a. *There is a positive relationship between managerial capabilities and the compatibility of AI.*

H3b. *There is a positive relationship between managerial capabilities and the relative advantage of AI.*

H3c. *There is a negative relationship between managerial capabilities and the complexity of AI.*

In addition, existing culture, practices, and processes influence managers' decision-making, including the decision to adopt AI. A manager's dominant logic also influences coordinating and facilitating new technology innovation. Therefore, the manager’s logic and support lead to the following hypotheses:

H3d. *There is a positive relationship between managerial capabilities and managerial support.*

H3e. *There is a positive relationship between managerial capabilities and technical capabilities.*

External environment

Government involvement

The use of AI introduces new challenges for an organisation, such as social ethics, privacy and regulatory boundaries around the use of data. Thus, AI requires a well-regulated environment (Chen et al., 2021). In response, government authorities could respond by imposing constraining regulations for organisations to manage these risks (Mariemuthu, 2019). The regulations could lead to AI adoption being less attractive for some organisations. This government-led regulatory contribution leads to the following hypothesis:

H4a. *There is a positive relationship between government involvement and AI adoption.*

Competitive pressure

Competitive pressure refers to the need for an organisation to take action to maintain a competitive advantage. Pressure from competitors can drive the adoption of new technologies in the market. Oliveira and Martins (2011) state that organisations feel pressure when a competitor adopts new technology and therefore adopt the technology to maintain their competitiveness. Therefore, competitive pressure leads to the following hypothesis:

H4b. *There is a positive relationship between competitive pressure and AI adoption.*

Market uncertainty

Market factors include the extent of competition in the market, the demand for products, and customer loyalty. Generally, these factors are out of the firm's control, but can affect the firm's performance. Although AI is still immature, it can provide companies with a more competitive advantage and an opportunity to shape the market. Therefore, market uncertainty leads to the following hypothesis:

***H4c**. There is a positive relationship between market uncertainty and AI adoption.*

Vendor partnership

Organisations usually require external support to implement new IT innovations. Implementation of emergent technologies such as AI is usually done through a third-party supplier, with some organisations relying on external parties for data services that support AI applications. Therefore, vendor partnership is important in the adoption of new technologies. Empirical studies also support that a vendor partnership is a critical determinant for innovation adoption (Ahmadi et al., 2015; Yang et al., 2013). Therefore, the potential for vendor partnerships leads to the following hypothesis:

***H4d.** There is a positive relationship between vendor partnership and AI adoption.*

Customer experience

Perceived ease of use (PEOU)

Perceived ease of use (PEOU) is the extent to which an individual assumes that the use of the new information system will be effortless (Chatzipavlou et al., 2015; Venkatesh & Bala, 2008). PEOU includes quality of service, simplicity, visual factors, speed, and innovativeness (Phan & Daim, 2011). The ease of use of AI-enabled services and applications depends on aspects such as design, functionality, speed, and availability of a service. In their study, Hong et al. (2006) found PEOU to positively influence user satisfaction in the context of information technology usage, and this agrees with other studies that found that PEOU can predict user satisfaction (Rod et al., 2009; Sun et al., 2008). Therefore, perceived ease of use leads to the following hypothesis:

H5: *Perceived ease of use has a positive impact on customer experience.*

Perceived usefulness (PU)

An individual's perception of the usefulness of technology depends on the extent to which they believe that using a particular technology will improve their task or job performance within an organisation. In the context of AI-enabled services and applications, such help may be realised through task automation or personalisation of services. Previous studies found that perceived usefulness is an important measure of customer satisfaction (Rod et al., 2009; Sharma et al., 2014; Sun et al., 2008). Therefore, perceived usefulness leads to the following hypothesis:

H6. *Perceived usefulness has a positive impact on customer experience.*

2.5 Rationale for the proposed theoretical framework for AI adoption

Previous studies on organisational technology adoption have integrated the TOE framework with DOI theory to isolate factors that influence organisational adoption of innovations (Chen, 2019; Mariemuthu, 2019; Oliveira & Martins, 2011; Piaralal et al., 2015; Rao, 2017). This study follows the same approach to investigate success factors for AI adoption by South African financial services companies. More than one theoretical model should be combined to understand the adoption of complicated innovation technologies (Mariemuthu, 2019; Oliveira & Martins, 2011). Previous studies have also used TAM to measure customer satisfaction when using technology

(Rod et al., 2009). Hence, this study integrates the DOI, TOE, and TAM frameworks and proposes an integrated theoretical framework for organising the research.

2.6 Conclusion of literature review

The reviewed literature addresses the research objective to understand factors that influence AI adoption by South African financial services organisations and understand how customers experience AI applications after adoption by financial institutions. Although studies on AI adoption by an organisation are limited, literature on IT adoption by organisations exists and forms the basis of the foundation of this study. Previous studies on IT adoption integrate the DOI theory and TOE framework to examine factors influencing IT (Chen, 2019; Mariemuthu, 2019; Oliveira & Martins, 2011; Oliveira et al., 2014; Piaralal et al., 2015; Rao, 2017). Therefore, this study also uses these frameworks to isolate AI-adoption factors. TOE identifies technological, organisational, and environmental contexts of adoption as key aspects influencing an organisation to adopt and implement technological innovation, while DOI identifies five factors that influence innovation, namely relative advantage, compatibility, complexity, trialability, and observability. These trialability and observability are not widely applied in past IT studies and is also not considered in this study. Past studies identified TAM as a valuable tool in forecasting customer satisfaction, improving customer service and improving service quality (Rod et al., 2009). In particular, ease of use and usefulness are important factors in evaluating online service quality. Therefore, this study uses the ease of use and usefulness to study customer experience after AI adoption by firms.

CHAPTER 3. RESEARCH METHODOLOGY

Chapter 3 outlines the methodology used to identify factors that influence the adoption of AI by South African financial services firms. The chapter begins by unpacking the methodology used, followed by the research instruments, population, and sample for this study. After that, data collection methods, analysis, and data interpretation techniques are outlined. Finally, the chapter ends with how the reliability and validity of the study were tested.

3.1 Research approach

The foundation of this study is quantitative, with a positivist interpretation, to statistically understand and infer the relationships between factors that influence AI adoption and adoption decisions and how customers experience AI applications after adoption by financial institutions. According to Creswell (2014), the quantitative research method is associated with the post-positivist worldview, where the primary philosophy is based on measuring outcomes scientifically.

Quantitative research tests objective theories by investigating the relationship between variables (Sidek, 2015). Generally, these variables are measured using instruments for analysing the numbered data using statistical procedures (Creswell, 2014; Sidek, 2015). Therefore, according to Golafshani (2003), researchers can use their deep knowledge within the specified field of study to identify and formulate testable hypotheses and contextualise the results.

The objectives of this study are to identify factors that influence AI adoption by South African financial services and understand how AI-enabled applications are received by users after adoption by the organisation. The statistical results allow the researcher to make certain inferences to predict AI adoption factors.

3.2 Research design

This research applied a quantitative design to test the research objectives, with data collected using online surveys, where respondents were sent a link to the survey. The results were coded into Microsoft Excel for data cleansing and to facilitate analysis and interpretation of the data.

A larger sample size was preferred to gain a deeper understanding and generalise the findings. A close-ended questionnaire was used due to its simplicity and ease of data collection from a wider variety of respondents across South African financial services companies. This chosen quantitative research design method has the following advantages and disadvantages:

Table 1: Advantages and disadvantages of the chosen quantitative research method

Advantages	**Disadvantages**
Ease of data collection and analysis	Respondents may misinterpret the questionnaire
Data can be collected from a large population of respondents	Possibility of lack of validity should the instrument not be properly tested
Quantifiability of the results of the questionnaire using statistical tools	No way to judge the accuracy and truthfulness of respondents
Data can be used to test the hypothesis	Researcher bias in questionnaire design
A more scientific and objective approach to data analysis than other forms of research	

3.3 Data collection methods

An electronic questionnaire was used to collect data from senior managers and employees of South African financial services organisations to measure AI adoption decisions. For customer experience, a separate questionnaire was used to collect data from external customers of financial services organisations including the Wits student population. The questionnaires were designed and pre-tested using existing AI and technology adoption instruments to improve the content and face validity. Pre-testing helps with ensuring that the wording on the instrument is simple to understand and removes biases (Bhattacherjee, 2012; Mariemuthu, 2019).

3.4 Population and sample

3.4.1 Population

The target population for this research was employees of South African financial services organisations to collect data about AI adoption decisions and external customers of financial services organisations, including the Wits student population, to collect data about customer experience from AI-enabled services and applications. While financial services employees are also customers of those financial services organisations, their experience of AI-enabled services may be biased due to their emotional connection to their employer. This emotional connection supported the decision to split the questionnaires between internal and external customers.

3.4.2 Sample and sampling method

This research used a simple random sampling method to select employees of South African financial services organisations. Random sampling is deemed the most appropriate as it does not focus on a specific group of individuals. For the AI adoption study, LinkedIn was used to identify employees of South African financial services organisations as it gives the ability to identify respondents' characteristics, such as position, location and level of education, allowing for a more generalisation. For the customer experience study, LinkedIn and the Wits student population were used to source respondents.

According to Hair (2009), the sample size should at least be five times the total indicators. The research model to measure AI adoption decision has 46 indicators, and the target sample size was 236. The research model to measure customer experience has 23 observed indicators, and the target sample size was 115.

3.5 Research instrument

The primary research instrument for this study was two questionnaires designed to collect data on AI adoption and user satisfaction. The questionnaires adapted items from previous studies on technology adoption and user satisfaction. A 7-point Likert scale was applied to measure the items, ranging from 1 (strongly disagree) to 7 (strongly agree).

Both questionnaires were divided into two sections:

1. Demographics information
2. Adoption of AI technologies factors/Customer-experience factors

Independent variables for this study are summarised in Table 2.

Table 2: Item construction summary for the AI adoption questionnaire

Construct	**Factors**	**Source**
Government involvement	The government supplies related information.	(Chen, 2019; Oliveira et al., 2014; Yang et al., 2013; Yang et al., 2015)
	The specification and stability of government policies are beneficial for business operations.	
	We should maintain a good relationship with the local government.	
	Government support and help are very important for us to innovate.	
Market uncertainty (deleted)	There is a trend in our industry to utilise more AI technologies for business development and applications. (deleted)	(Chau & Tam, 1997; Chen, 2019)
	Only innovative technologies can help our company to provide perfect products and services to meet the growing personalised needs of consumers. (deleted)	
	AI has broad application prospects in our industry. (deleted)	
	AI can help our company to gain competitiveness. (deleted)	
Competitive pressure	The rate of innovation of new operating processes and new products and services in our industry has increased dramatically.	(Chang et al., 2006; Chen, 2019)
	An industry move to utilise AI technologies would pressure our company to do the same. (deleted)	
	There is tough price competition in our industry.	
	There is tough competition on product/service quality in our industry.	
Vendor partnership	We have had no difficulty obtaining assistance or reliable services from our vendors/partners.	(Chen, 2019; Han et al., 2008; Zhu et al., 2003)
	Our technology partners are trustworthy.	
	We have very close relationships with vendors/technology partners.	
	Our vendors/partners are knowledgeable about AI technologies.	
Managerial capability	We have clear goals and objectives to adopt AI technology innovation.	(Chen, 2019; Garrison et al., 2015)
	Inter-department cooperation is very important to adopt AI technology innovation.	
	Inter-department communication is very important to adopt AI technology innovation.	
	Formal education and training programmes can be developed to include all classes of users ranging from managers to shop floor controllers. (deleted)	
Managerial support	Managers are willing to take risks involved in the adoption of AI.	(Chen, 2019; Garrison et al.,
	Our managers have the ability to exploit new technologies before our competitors.	

	Our managers have the ability to leverage IT new technologies as a strategic core competence. (deleted)	2015; Han et al., 2008)
	Our managers have a strong understanding of how AI technology can increase business performance.	
	Senior managers explicitly demonstrate to support the adoption of AI.	
Technical capability	We have a standardised process for IT innovation.	(Chen, 2019; Garrison et al., 2015; Han et al., 2008)
	We can quickly integrate new AI technologies into our existing infrastructure.	
	Our IT strategies support our business strategies.	
	We have suitable hardware/software to protect the security and privacy of our systems and networks.	
Compatibility	AI applications are compatible with our current communication/network environment.	(Chang et al., 2006; Chen, 2019; Chong et al., 2009)
	AI applications are compatible with our current software environment.	
	AI applications are compatible with our current hardware environment.	
	AI application is compatible with our infrastructure.	
	AI application is compatible with computerised data resources.	
Relative advantage	AI applications can increase employee productivity.	(Chen, 2019; Chong et al., 2009; Thong, 1999)
	AI applications can improve customer service.	
	AI applications can better utilise IT resources.	
	AI applications can promote flexibility and integration.	
Complexity	Adopting AI innovation lacks application maturity.	(Chen, 2019; Chong et al., 2009; Thong, 1999)
	There is a high cost for AI application and migration.	
	Adopting AI innovation is time-consuming.	
	Inappropriate staffing and personnel shortfalls are a big issue for adopting AI innovation. (deleted)	
AI adoption	A timely AI technical implementation and application migration plan has been developed.	(Chau & Tam, 1997; Chen, 2019)
	The plan has already been endorsed by managers.	
	A financial budget and a migration schedule were approved.	
	Our customers readily accept new products and services using AI innovations.	
	Our competitive position improves after adopting AI innovations.	
Construct	**Factors**	**Source**

Government involvement	The government supplies related information.	(Chen, 2019; Oliveira et al., 2014; Yang et al., 2013; Yang et al., 2015)
	The specification and stability of government policies are beneficial for business operations.	
	We should maintain a good relationship with the local government.	
	Government support and help are very important for us to innovate.	
Market uncertainty (deleted)	There is a trend in our industry to utilise more AI technologies for business development and applications. (deleted)	(Chau & Tam, 1997; Chen, 2019)
	Only innovative technologies can help our company to provide perfect products and services to meet the growing personalised needs of consumers. (deleted)	
	AI has broad application prospects in our industry. (deleted)	
	AI can help our company to gain competitiveness. (deleted)	
Competitive pressure	The rate of innovation of new operating processes and new products and services in our industry has increased dramatically.	(Chang et al., 2006; Chen, 2019)
	An industry move to utilise AI technologies would pressure our company to do the same. (deleted)	
	There is tough price competition in our industry.	
	There is tough competition on product/service quality in our industry.	
Vendor partnership	We have had no difficulty obtaining assistance or reliable services from our vendors/partners.	(Chen, 2019; Han et al., 2008; Zhu et al., 2003)
	Our technology partners are trustworthy.	
	We have very close relationships with vendors/technology partners.	
	Our vendors/partners are knowledgeable about AI technologies.	
Managerial capability	We have clear goals and objectives to adopt AI technology innovation.	(Chen, 2019; Garrison et al., 2015)
	Inter-department cooperation is very important to adopt AI technology innovation.	
	Inter-department communication is very important to adopt AI technology innovation.	
	Formal education and training programmes can be developed to include all classes of users ranging from managers to shop floor controllers. (deleted)	
Managerial support	Managers are willing to take risks involved in the adoption of AI.	(Chen, 2019; Garrison et al., 2015; Han et al., 2008)
	Our managers have the ability to exploit new technologies before our competitors.	
	Our managers have the ability to leverage IT new technologies as a strategic core competence. (deleted)	
	Our managers have a strong understanding of how AI technology can increase business performance.	
	Senior managers explicitly demonstrate to support the adoption of AI.	

Technical capability	We have a standardised process for IT innovation.	(Chen, 2019; Garrison et al., 2015; Han et al., 2008)
	We can quickly integrate new AI technologies into our existing infrastructure.	
	Our IT strategies support our business strategies.	
	We have suitable hardware/software to protect the security and privacy of our systems and networks.	
Compatibility	AI applications are compatible with our current communication/network environment.	(Chang et al., 2006; Chen, 2019; Chong et al., 2009)
	AI applications are compatible with our current software environment.	
	AI applications are compatible with our current hardware environment.	
	AI application is compatible with our infrastructure.	
	AI application is compatible with computerised data resources.	
Relative advantage	AI applications can increase employee productivity.	(Chen, 2019; Chong et al., 2009; Thong, 1999)
	AI applications can improve customer service.	
	AI applications can better utilise IT resources.	
	AI applications can promote flexibility and integration.	
Complexity	Adopting AI innovation lacks application maturity.	(Chen, 2019; Chong et al., 2009; Thong, 1999)
	There is a high cost for AI application and migration.	
	Adopting AI innovation is time-consuming.	
	Inappropriate staffing and personnel shortfalls are a big issue for adopting AI innovation. (deleted)	
AI adoption	A timely AI technical implementation and application migration plan has been developed.	(Chau & Tam, 1997; Chen, 2019)
	The plan has already been endorsed by managers.	
	A financial budget and a migration schedule were approved.	
	Our customers readily accept new products and services using AI innovations.	
	Our competitive position improves after adopting AI innovations.	

Table 3: Item construction summary for the customer experience questionnaire

Construct	Factors	Source
Perceived Usefulness	The use of AI in financial services allows me to find the best products.	(Weng et al., 2018)
	The use of AI in financial services is useful to me.	
	The use of AI in financial services allows a personalised experience.	
	The use of AI in financial services helps me access financial information more quickly.	
	The use of AI in financial services saves time.	
Perceived Ease of Use	AI-powered applications (e.g. chatbots, virtual assistants, etc.) are easy to use.	(Weng et al., 2018)
	It is easy for me to become skilful at AI-powered applications.	
	I find AI-powered applications to be flexible to interact with	
	My interaction with AI-powered applications is clear and understandable.	
	Using financial products is easy if supported by AI.	
Attitude towards using	Using AI in financial services is a good idea.	(Weng et al., 2018)
	Using AI in financial services is a wise idea.	
	I think it is valuable to use AI in financial services.	
	I think it is a trend to use AI in financial services.	
	I am positive about AI-powered applications in financial services.	
User Satisfactions	It is fun and enjoyable when AI helps me to find the best-suited products.	(Abu-Dalbouh, 2013)
	I believe that using AI has improved the quality of the financial service industry.	
	I am completely satisfied with the use of AI in financial services.	
Overall Customer Experience	My overall experience of using AI-powered applications in financial services was: • Educational • Exciting • Memorable • Entertaining • Comfortable	(Ameen et al., 2021)

3.6 Procedure for data collection

Online questionnaires were sent to the target populations via a link to the online survey. Only one response per computer was allowed. Completed responses were automatically uploaded to a central database. Incomplete questionnaires were also tracked; however, they were deleted from the final dataset used to analyse the results.

3.7 Data analysis and interpretation

The data was extracted from the online surveys, exported into Microsoft Excel, and then loaded onto SmartPLS for analysis. Exploratory data analysis (EDA) was performed using Excel to understand the distribution of the demographic variables. According to Alchemer (2018), researchers who conduct exploratory data analysis identify errors made in data collection and areas where data may be missing, map the underlying structure of the data, identify the most influential variables in the data set, and list and highlight anomalies and outliers.

Structural equation modelling (SEM) was used to analyse the data from both surveys. SEM is a multivariate technique to test causal relationships between variables. According to Schulze (2009), the second-generation multivariate research techniques explicitly account for measurement error, analyse complex research models with multiple predictors and criterion variables, and allow for the measurement of latent variables that are not directly observable.

3.8 Limitations of the study

- This study focuses on financial services organisations in South Africa. Factors examined may not apply to other industries.

- The AI-adoption study had low responses (70). A larger sample size could have a different influence on some observed relationships between latent factors and AI adoption.
- The quality of data received could be compromised due to the length of the questionnaires.
- The questionnaires were completed without the presence of the researchers, thus subjected to the respondent's own interpretation.
- The focus of this study was on the South African financial services organisations. Therefore, the AI-adoption factors observed in this study only reflect situations in one industry and one nation.
- Moreover, 82% of respondents are from banking and adoption decisions reflected in this study mainly relate to banking. Other financial services sub-industries are underrepresented.

3.9 Validity and reliability

Heale and Twycross (2015) defines validity as the extent to which a concept is accurately measured in a quantitative study. Reliability is defined as the extent to which a research instrument consistently has the same results if used in the same situation on repeated occasions (Heale & Twycross, 2015). The external validity, internal validity and reliability of the research are highlighted in the following sections.

3.9.1 External validity or transferability

External validity refers to the generalisability of findings from a study or the extent to which conclusions can be applied across different populations or situations (McDermott, 2011). Because this study is limited to South African financial services organisations, the findings of this study may not apply to other industries and geographies.

3.9.2 Internal validity

Internal validity refers to the ability of a research instrument to measure what it is intended to measure (Blumberg et al., 2014). This study adopts tested survey questions from previous imperial studies on AI adoption by organisations and user satisfaction to maximise the validity of the research.

3.9.3 Reliability

Reliability is defined as the degree to which results are consistent over time (Blumberg et al., 2011). Cronbach alpha tests were performed on the data to determine how well multiple items measure a single construct. These tests assist in determining if the reliability measures improve when certain items are removed. The data collection methods were consistent across all participants in the target population to improve the reliability of the study.

3.10 Ethical considerations

The Wits Business School Ethics Committee approved this study with protocol number WBS/DB0314719J/917. The ethics clearance certificate is contained in Appendix C. The study adhered to strict ethical principles of voluntary participation, informed consent, anonymity, and confidentiality. The cover letter that advises potential respondents of the objective of the study is contained in Appendix B.

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

Chapter 4 presents the factors identified that influence the adoption of AI by South African financial services organisations and how customers experience AI-enabled products and services after adoption by financial services organisations. The chapter begins with data screening, followed by the tests of reliability and validity of the constructs. Lastly, hypothesis testing is presented based on structural equation modelling (SEM).

4.2 Data screening

Two online questionnaires were used to collect the data to measure AI adoption decisions in South African financial services organisations and to measure how customers experience AI-enabled products and services. For AI adoption, a total of 70 responses were received. Of the 70, there were 8 (11%) responses with incomplete data. The incomplete responses were removed from the final data set to ensure the accuracy of the analysis. Thus, the AI adoption final sample was 62. A breakdown of the survey responses is summarised in Table 4.

Table 4: Survey responses summary for AI adoption decisions

Total responses	Complete	Incomplete
70	62 (89%)	8 (11%)

For customer experience, there were 561 responses received. Of the 561, there were 154 (27%) responses with incomplete data and these were removed from the final dataset. Thus, the customer experience final sample was 407 and is summarised in Table 5.

Table 5: Survey responses summary for customer experience

Total responses	Complete	Incomplete
561	407 (73%)	154 (27%)

4.3 Validity and reliability

4.3.1 AI adoption validity and reliability

SmartPLS (Ringle et al., 2015) was used to measure the reliability of individual items and the construct validity of the measurement instrument. First, confirmatory factor analysis identified and confirmed the indicators under each construct regarding AI adoption. The results of factor analysis indicated that some items had to be eliminated as they either had low factor loadings (<0.4) or were cross loading on multiple factors. The factor loadings for the hypothesised model are presented in Figure 16 (Appendix E).

The construct reliability and validity results for the hypothesised model are presented in Table 15 (Appendix E). The results show a problem with some constructs items regarding internal reliability as some of Cronbach's alpha values were less than 0.7. According to Samuels (2017), the rule of thumb for an acceptable Cronbach's alpha coefficient value is 0.7 and above, although in some cases 0.6 is considered acceptable for exploratory work. There was also no convergent validity for managerial capacity and market uncertainty on the hypothesised model as the average variance extracted (AVE) values were less than the minimum acceptable value of at least 0.5 (Abma et al., 2016). This indicated a need to prune some items from the model to improve reliability and validity. Therefore, items with low factor loadings or were cross loading on multiple factors were eliminated. There was also no valid construct for market uncertainty, and thus the construct was eliminated from the model.

The factor loadings of the pruned model are presented in Figure 6 and confirm the significance of all paths between the remaining observed variables.

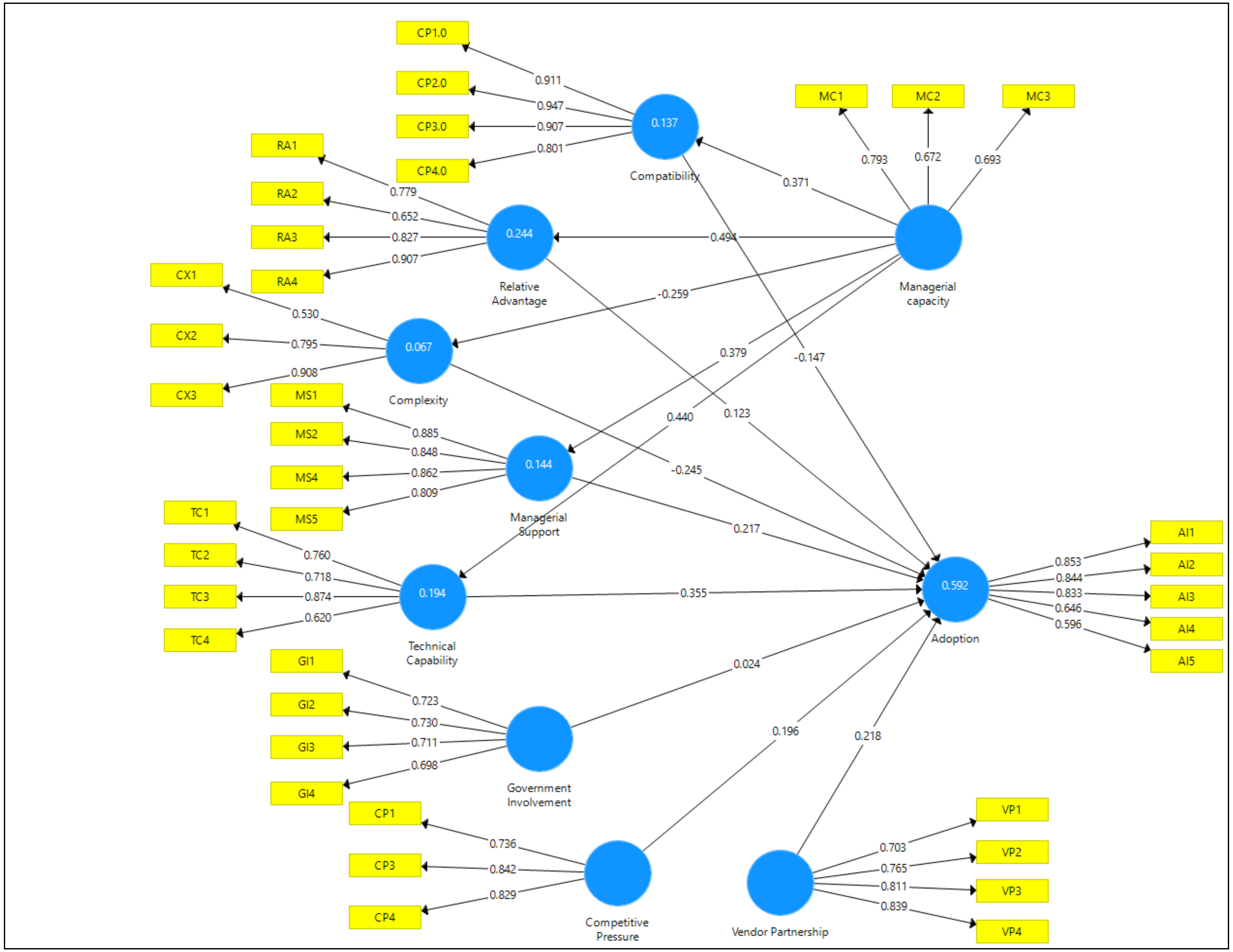

Figure 6: CFA – final AI adoption model

Table 6 presents the construct reliability and validity for the pruned model. Majority of the constructs show adequate levels of reliability and validity, with few showing slightly low construct reliability.

Table 6: Construct reliability and validity – final model

	Cronbach's alpha	Rho_a	Composite reliability	Average variance extracted (AVE)
Adoption	0.813	0.829	0.872	0.581
Compatibility	0.915	0.931	0.940	0.798
Competitive pressure	0.727	0.723	0.845	0.646
Complexity	0.677	0.906	0.798	0.580
Government involvement	0.687	0.691	0.808	0.513
Managerial support	0.874	0.885	0.913	0.725
Managerial capacity	0.642	0.645	0.764	0.520
Relative advantage	0.807	0.844	0.873	0.635
Technical capability	0.734	0.776	0.834	0.560
Vendor partnership	0.792	0.845	0.862	0.610

The Fornell-Larcker criterion was used to measure the divergent validity. According to the Fornell-Larcker criterion, the square root of each construct's AVE should be higher than its correlation with another construct (Henseler et al., 2015). There was generally divergent validity as the diagonal elements of the Fornell-Larcker criterion (Table 7) were greater than the off-diagonal correlations with other constructs.

Table 7: Fornell-Larcker criterion – final model

	Adoption	Compatibility	Competitive pressure	Complexity	Government involvement	Managerial support	Managerial capacity	Relative advantage	Technical capability	Vendor partnership
Adoption	0.762									
Compatibility	0.439	0.893								
Competitive pressure	0.484	0.233	0.804							
Complexity	-0.246	-0.052	-0.050	0.761						
Government involvement	0.187	0.228	0.415	0.150	0.716					
Managerial support	0.561	0.656	0.404	0.125	0.269	0.851				
Managerial capacity	0.526	0.371	0.221	-0.259	0.053	0.379	0.721			
Relative advantage	0.350	0.313	0.064	-0.043	0.043	0.276	0.494	0.797		
Technical capability	0.615	0.696	0.352	-0.026	0.223	0.694	0.440	0.368	0.748	
Vendor partnership	0.521	0.431	0.365	-0.068	0.043	0.482	0.470	0.268	0.392	0.781

4.3.2 Customer experience validity and reliability

Figure 7 presents the factor loadings from confirmatory factor analysis for the customer experience sample. The results showed high factor loadings across all items, thus confirming the significance of causal relations among observed variables.

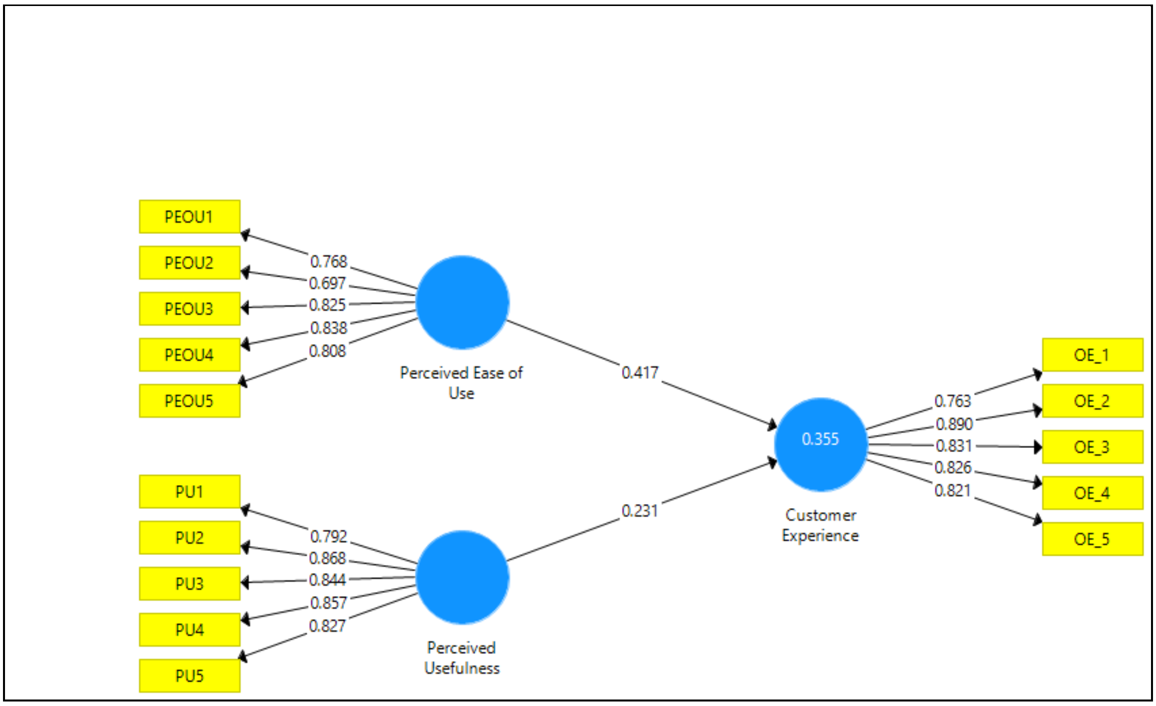

Figure 7: Customer experience CFA

There was general construct reliability as the Cronbach's alpha values (Table 8) were more than 0.7 across the various constructs. The average variance extracted (AVE) values were all larger than the recommended threshold of 0.50 (Abma et al., 2016), thus indicating a good convergent validity. Therefore, the model reliability and validity are met.

Table 8: Construct reliability and validity – customer experience

	Cronbach's alpha	**Rho_a**	**Composite reliability**	**Average variance extracted (AVE)**
Customer experience	0.884	0.892	0.915	0.684
Perceived ease of use	0.850	0.871	0.891	0.622
Perceived usefulness	0.894	0.898	0.922	0.702

There generally was divergent validity as the diagonal elements of the Fornell-Larcker criterion were greater than the off-diagonal correlations with other constructs (Table 9).

Table 9: Fornell-Larcker criterion – customer experience

	Customer experience	Perceived ease of use	Perceived usefulness
Customer experience	0.827		
Perceived ease of use	0.570	0.789	
Perceived usefulness	0.506	0.659	0.838

4.4 Hypothesis testing

Structural equation modelling (SEM) was used to evaluate the model to assess if it was fit to fulfil the study objective. SEM is a multivariate technique used to measure and analyse the relationships of observed and latent variables (Beran & Violato, 2010). In this study, variance-based structural equation modelling (PLS-SEM) was applied. According to Wong (2013), PLS-SEM is preferable when dealing with small sample sizes. The hypotheses were validated by bootstrapping with 2 000 re-samples. According to Streukens and Leroi-Werelds (2016), non-parametric bootstrapping does not rely on distributional assumptions and thus produces more robust results.

The path coefficient of the inner model can be checked for significance using a two-tailed t-test with a significance level of 5% (Hasan et al., 2015). The two-tailed t-test with a significance level of 5% establishes if the path coefficient will be significant if the t-statistics are larger than 1.96 (Wong, 2013).

4.4.1 Dependent variable AI adoption

Figure 8 depicts structural path significance in bootstrapping. The hypothesised path relationships between AI adoption and six of the observed variables (compatibility, competitive pressure, government involvement, managerial support, relative advantage, and vendor partnership) are less than 1.96, and are thus not significant. All other path coefficients in the inner model are statistically significant.

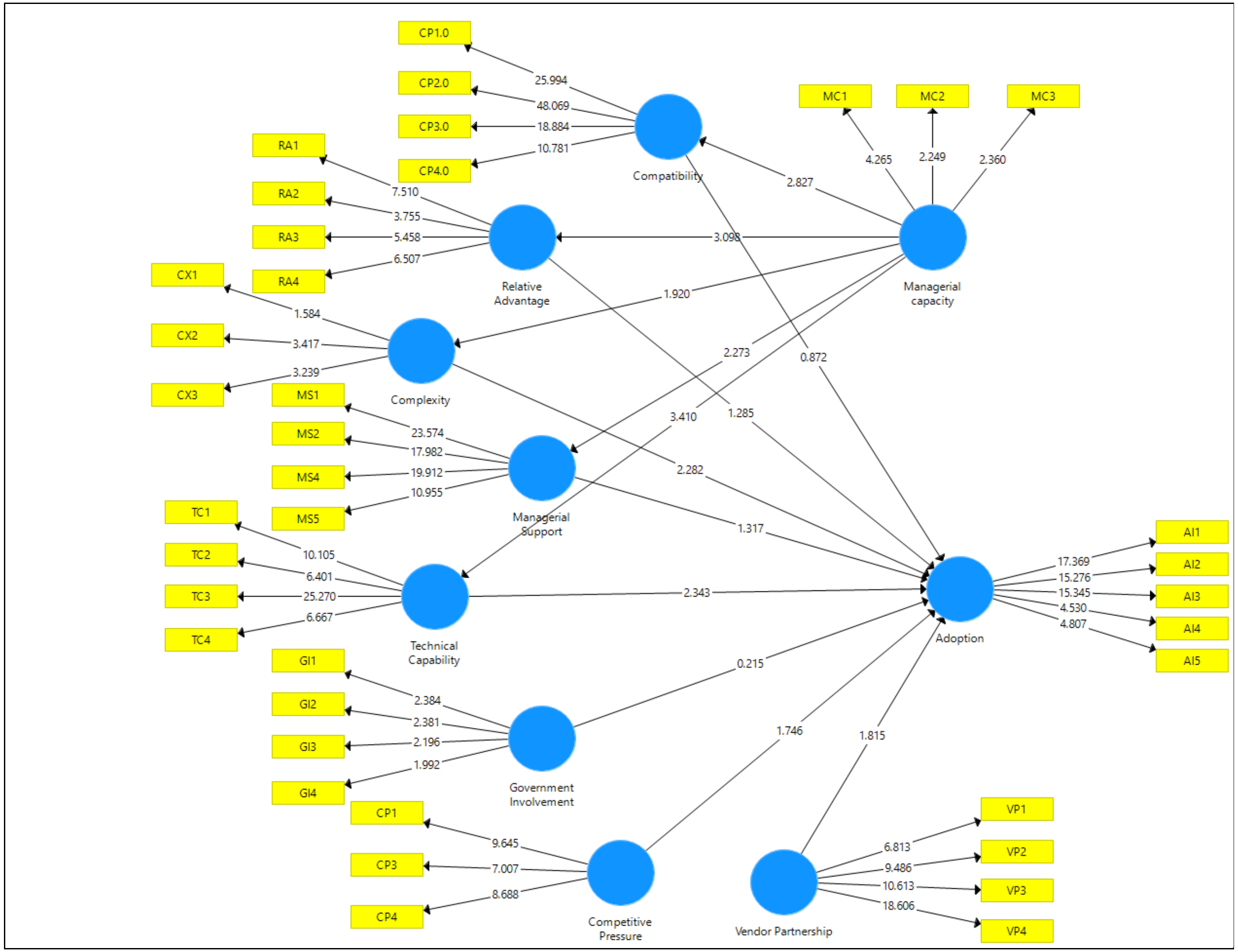

Figure 8: Structural equation modelling (SEM) – dependent variable AI adoption

Table 10: Mean, standard deviation, t-values, p-values – dependent variable AI adoption

	Original sample (o)	**Sample mean (m)**	**Standard deviation (STDEV)**	**T-statistics (|o/STDEV|)**	***P-values***	**Hypothesis testing results**
Compatibility -> AI adoption	-0.150	-0.105	0.173	0.872	0.383	Not Supported
Competitive pressure -> AI adoption	0.197	0.186	0.114	1.729	0.084	Supported
Complexity -> AI adoption	-0.245	-0.221	0.107	2.287	0.022	Supported
Government involvement -> AI adoption	0.024	0.043	0.108	0.217	0.828	Supported
Managerial support -> AI adoption	0.218	0.187	0.162	1.344	0.179	Supported
Managerial capability -> compatibility	0.371	0.388	0.127	2.929	0.003	Supported
Managerial capability -> complexity	-0.259	-0.271	0.131	1.985	0.047	Supported
Managerial capability -> managerial support	0.379	0.390	0.159	2.382	0.017	Supported
Managerial capability -> relative advantage	0.494	0.482	0.167	2.968	0.003	Supported
Managerial capability -> technical capability	0.440	0.446	0.123	3.585	0.000	Supported
Relative advantage -> AI adoption	0.121	0.107	0.091	1.327	0.185	Supported
Technical capability -> AI adoption	0.358	0.347	0.149	2.399	0.017	Supported
Vendor partnership -> AI adoption	0.219	0.229	0.123	1.779	0.075	Supported

Table 10 shows the hypothesis testing results. A *p-value* less than 0.05 (typically ≤ 0.05) is statistically significant and indicates strong evidence against the null hypothesis, while a *p-value* higher than 0.05 (> 0.05) is not statistically significant and indicates strong evidence for the null hypothesis (McLeod, 2019).

Results related to Hypothesis H1a. *There is a positive relationship between compatibility and AI adoption.*

The results show that compatibility (B = -0.150, *p-value* = 0.383) had a negative but insignificant effect on AI adoption. Thus, hypothesis H1a was not supported, but the result was not significant (*p-value* > 0.05).

Results related to Hypothesis H1b. *There is a positive relationship between relative advantage and AI adoption.*

The results show that relative advantage (B = 0.121, *p-value* = 0.185) had a positive but insignificant effect on AI adoption. Thus, hypothesis H1b was supported, but the result was not significant (*p-value* > 0.05).

Results related to Hypothesis H1c. *There is a negative relationship between complexity and AI adoption.*

The results show that complexity (B = -0.245, *p-value* = 0.022) had a negative and significant effect on AI adoption. Thus, hypothesis H1c was supported and the result was significant (*p-value* $\leq$ 0.05).

Results related to Hypothesis H2a. *There is a positive relationship between managerial support and AI adoption.*

The results show that managerial support (B = 0.218, *p-value* = 0.179) had a positive but insignificant effect on AI adoption. Thus, hypothesis H2a was supported, but the result was not significant (*p-value* > 0.05).

Results related to Hypothesis H2b. *There is a positive relationship between technical capabilities and AI adoption.*

The results show that technical capabilities (B = 0.358, *p-value* = 0.017) had a positive and significant effect on AI adoption. Thus, hypothesis H2b was supported, and the result was significant (*p-value* $\leq$ 0.05).

Results related to Hypothesis H3a. *There is a positive relationship between managerial capabilities and the compatibility of AI.*

The results show that managerial capabilities (B = 0.371, *p-value* = 0.003) had a positive and significant effect on the compatibility of AI. Thus, hypothesis H3a was supported, and the result was significant (*p-value* $\leq$ 0.05).

Results related to Hypothesis H3b. *There is a positive relationship between managerial capabilities and the relative advantage of AI.*

The results show that managerial capabilities (B = 0.494, *p-value* = 0.003) had a positive and significant effect on relative advantage. Thus, hypothesis H3b was supported, and the result was significant (*p-value* $\leq$ 0.05).

Results related to Hypothesis H3c. *There is a negative relationship between managerial capabilities and the complexity of AI.*

The results show that managerial capabilities (B = -0.259, *p-value* = 0.047) had a negative and significant effect on the complexity of AI. Thus, hypothesis H3c was supported, and the result was significant (*p-value* $\leq$ 0.05).

Results related to Hypothesis H3d. *There is a positive relationship between managerial capabilities and managerial support.*

The results show that managerial capabilities (B = 0.379, *p-value* = 0.017) had a positive and significant effect on managerial support. Thus, hypothesis H3d was supported, and the result was significant (*p-value* $\leq$ 0.05).

Results related to Hypothesis H3e. *There is a positive relationship between managerial capabilities and technical capabilities.*

The results show that managerial capabilities (B = 0.440, *p-value* = 0.000) had a positive and significant effect on technical capability. Thus, hypothesis H3e was supported, and the result was significant (*p-value* $\leq$ 0.05).

Results related to Hypothesis H4a. *There is a positive relationship between government involvement and AI adoption.*

The results show that government involvement (B = 0.024, *p-value* = 0.828) had a positive but insignificant effect on AI adoption. Thus, hypothesis H4a was supported, but the result was not significant (*p-value* > 0.05).

Results related to Hypothesis H4b. *There is a positive relationship between competitive pressure and AI adoption.*

The results show that competitive pressure (B = 0.197, *p-value* = 0.084) had a positive but insignificant effect on AI adoption. Thus, hypothesis H4b was supported, but the result was not significant (*p-value* > 0.05).

Results related to Hypothesis H4c. *There is a positive relationship between market uncertainty and AI adoption.*

There was no valid construct for market uncertainty, and therefore it was removed from the final model.

Results related to Hypothesis H4d. *There is a positive relationship between vendor partnership and AI adoption.*

The results show that vendor partnership (B = 0.219, *p-value* = 0.075) had a positive but insignificant effect on AI adoption. Thus, hypothesis H4d was supported, but the result was not significant (*p-value* > 0.05).

4.4.2 Dependent variable customer experience

Figure 9 depicts structural path significance in bootstrapping. The results show that the hypothesised paths' relationship between customer experience and perceived ease of use is statistically significant (t-statistics = 6.721). In addition, the hypothesised path relationship between customer experience and perceived usefulness is statistically significant (t-statistics = 3.832).

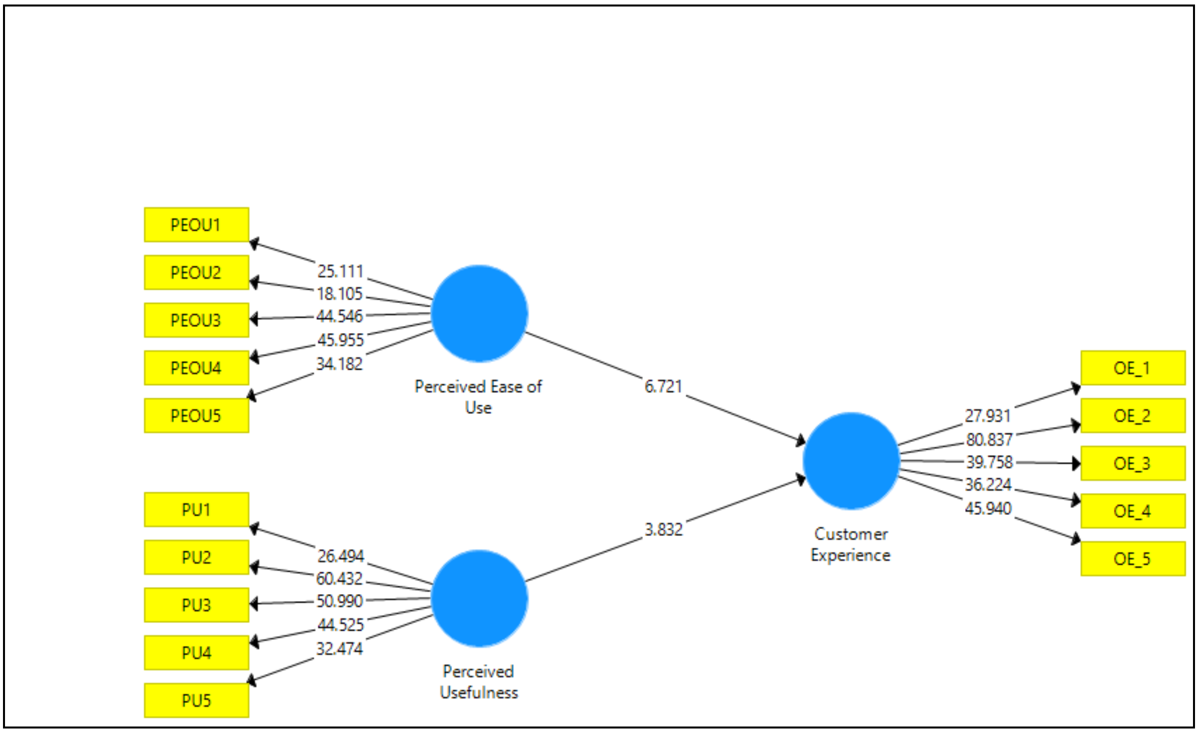

Figure 9: Customer experience (structural equation modelling [SEM]) – dependent variable customer experience

Table 11 shows the hypotheses testing results. A *p-value* less than 0.05 (typically ≤ 0.05) is statistically significant and indicates strong evidence against the null hypothesis. In contrast, a *p-value* higher than 0.05 (> 0.05) is not statistically significant and indicates strong evidence for the null hypothesis (McLeod, 2019).

Table 11: Mean, standard deviation, t-values, p-values – dependent variable customer experience

	Original sample (o)	Sample mean (m)	Standard deviation (STDEV)	T-statistics (|o/STDEV|)	*P-values*	Hypothesis testing
Perceived ease of use -> customer experience	0.417	0.420	0.062	6.721	0.000	Supported
Perceived usefulness -> customer experience	0.231	0.231	0.060	3.832	0.000	Supported

Results related to Hypothesis H5: *Perceived ease of use has a positive impact on customer experience.*

The results show that perceived ease of use (B = 0.417, *p-value* = 0.000) had a positive and significant effect on customer experience. Thus, hypothesis H5 was supported, and the result was significant (*p-value* $\leq$ 0.05).

Results related to Hypothesis H6: *Perceived usefulness has a positive impact on customer experience.*

The results show that perceived usefulness (B = 0.231, *p-value* = 0.000) had a positive and significant effect on customer experience. Thus, hypothesis H6 was supported, and the result was significant (*p-value* $\leq$ 0.05).

4.5 Summary of the results

In this chapter, the results of data analysis were presented from the sample datasets. The datasets were the factors influencing AI adoption in South African financial services organisations and how customers experience AI-enabled products and services after adoption by financial services organisations. The results included the presentation of respondents' profiles for both AI-adoption factors and customer-experience factors. Validity and reliability tests were carried out along with hypothesis testing based on SEM. The factor analysis results for AI-adoption factors indicated that some items had to be eliminated as the AI-adoption factors either had low factor loadings (<0.4) or were cross loading on multiple factors. There was also no valid construct for market uncertainty, and therefore it was removed from the final model. The hypotheses were validated by bootstrapping with 2 000 re-samples using PLS-SEM, and the results are summarised in Table 12 (AI adoption factors) and Table 13 (customer experience factors).

Table 12: Summary results - AI adoption

Hypothesis		**Hypothesis testing**
H1a	Compatibility -> AI adoption	Not supported
H1b	Relative advantage -> AI adoption	Supported
H1c	Complexity -> AI adoption	Supported
H2a	Managerial support -> AI adoption	Supported
H2b	Technical capability -> AI adoption	Supported
H3a	Managerial capacity -> Complexity	Supported
H3b	Managerial capacity -> Relative Advantage	Supported
H3c	Managerial capacity -> Complexity	Supported
H3d	Managerial capacity -> Managerial Support	Supported
H3e	Managerial capacity -> Technical Capability	Supported
H4a	Government involvement -> AI adoption	Supported
H4b	Market uncertainty -> AI adoption	Unable to evaluate
H4c	Competitive pressure -> AI adoption	Supported
H4d	Vendor partnership -> AI adoption	Supported

Table 13: Summary results: Customer experience

Hypothesis		**Hypothesis testing**
H5	Perceived ease of use -> customer experience	Supported
H6	Perceived usefulness -> customer experience	Supported

CHAPTER 5. DISCUSSION OF THE RESULTS

5.1 Introduction

Chapter 5 presents an in-depth analytical discussion of the data analysis results presented in Chapter 4. The chapter begins by presenting the demographic profiles of respondents for both the AI-adoption factor instrument and the customer experience instrument. After that, an in-depth discussion of results is presented pertaining to hypotheses testing for both the AI-adoption study and the customer experience study.

5.2 Demographic profile of the respondents

5.2.1 AI adoption sample

Age of the respondent

Figure 10 presents the breakdown of respondents by age group.

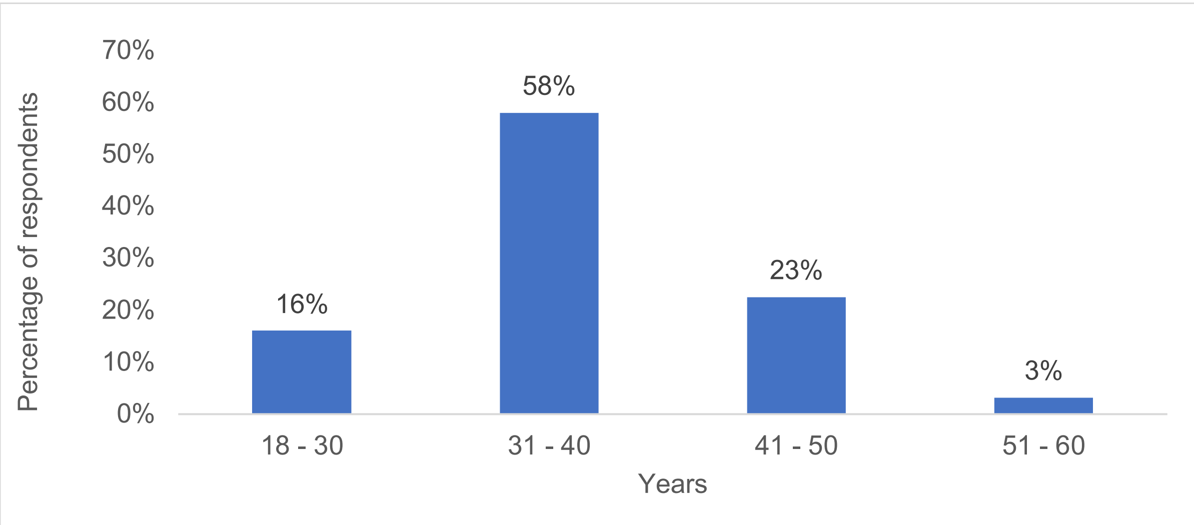

Figure 10: Respondents' age

The analysis by the age of respondents shows that the majority of the respondents are between 31 and 40 (58%) years, followed by those between 41 and 50 (23%) years and those between 51 and 60 (3%) years.

Level of education

Figure 11 presents a distribution of respondents based on their level of education. The majority of respondents have a postgraduate qualification (68%), followed by those with a bachelor's degree (21%) and those with a national diploma (23%). All these respondents were considered relevant for this study.

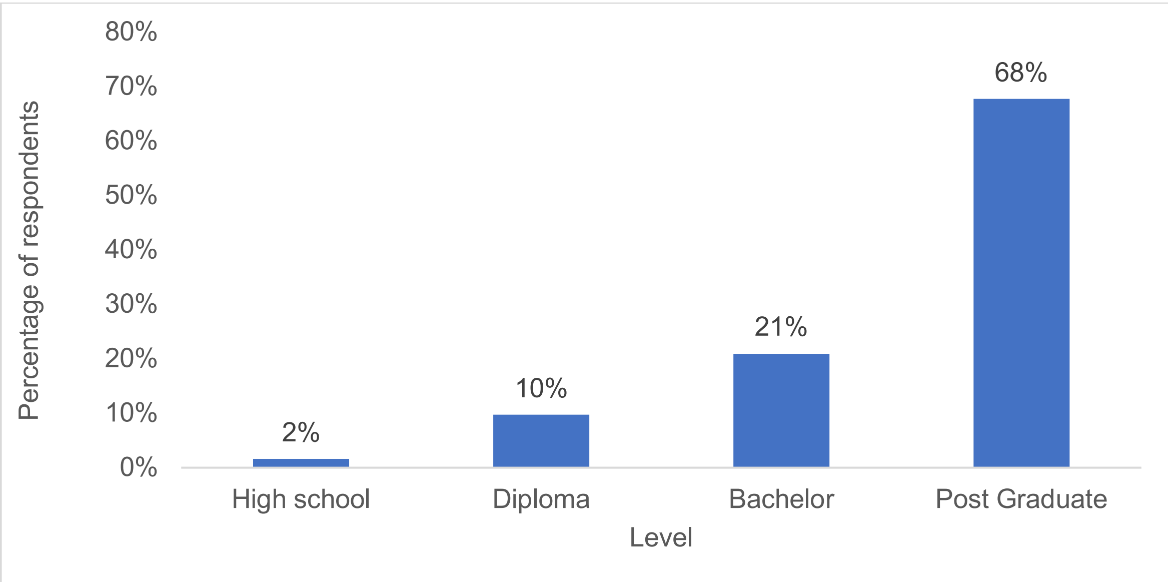

Figure 11: Level of education

Number of years in current role

Figure 12 presents a distribution of respondents based on the number of years in their current role. The majority of respondents have been in their roles between two and four years (50%), followed by five and seven years (16%), less than a year (15%), between eight and ten years (10%), and more than ten years (10%).

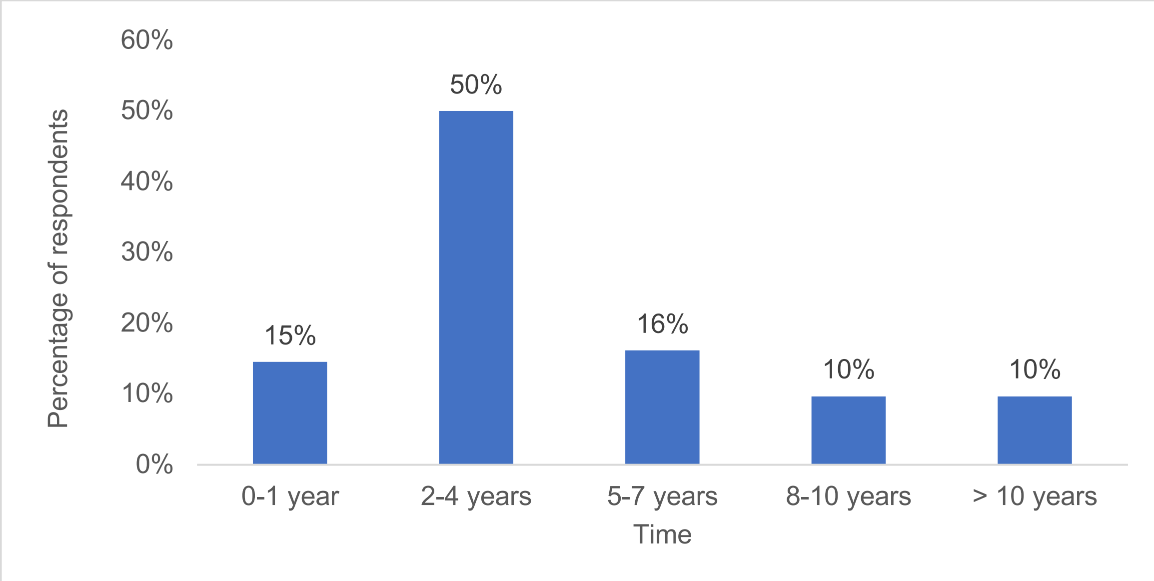

Figure 12: Number of years in current role

Number of years in organisation

Figure 13 presents a distribution of respondents based on the number of years in their organisation. The results show a fair representation of all the categories in the sample. Respondents who have been in their organisations between two and four years (27%), followed by over ten years (26%), between five and seven years (23%), and eight to ten years (10%) are least represented.

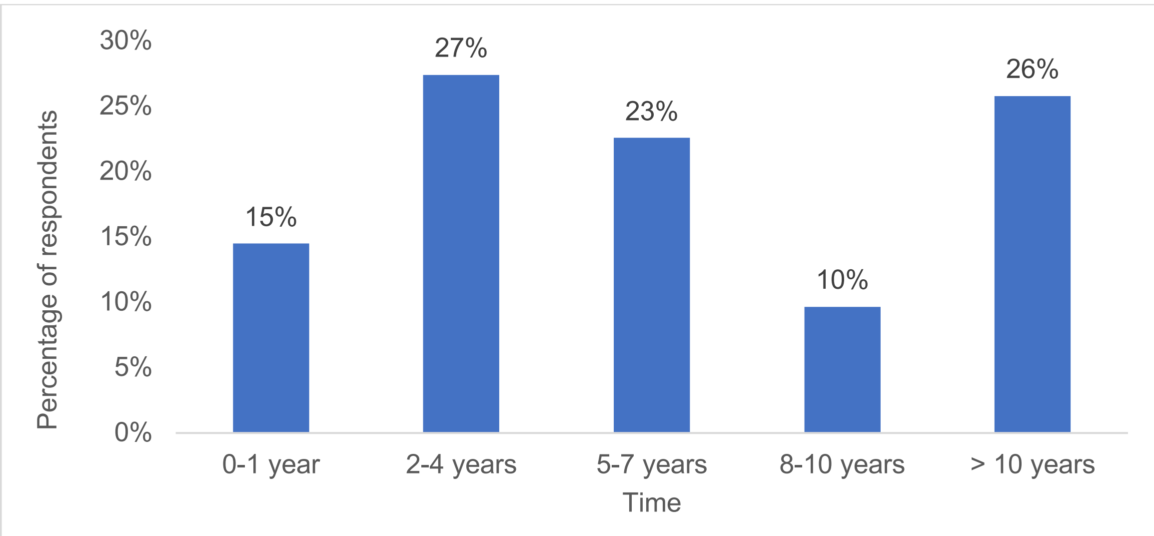

Figure 13: Number of years in organisation

Type of organisation

Figure 14 presents a distribution of respondents based on the type of their organisation. The vast majority of the respondent works for banks (82%), followed by insurance companies (6%), with a minimal representation of other financial services sub-industries.

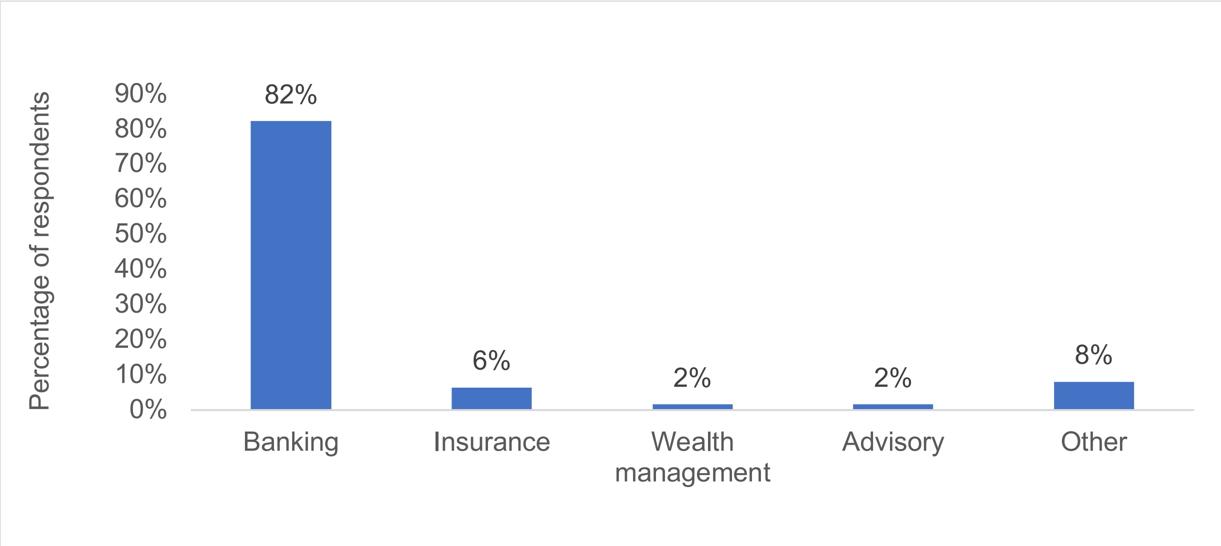

Figure 14: Type of organisation

Number of employees

Figure 15 presents a distribution of respondents based on the size of their organisation. The vast majority of the respondents work in large organisations with more than 5000 employees (84%). These are organisations such as banks and insurance organisations. Few respondents represented smaller organisations with under 500 employees (6%), and medium-sized organisations with between 500 and 2000, and 3501 and 5000 (~9%).

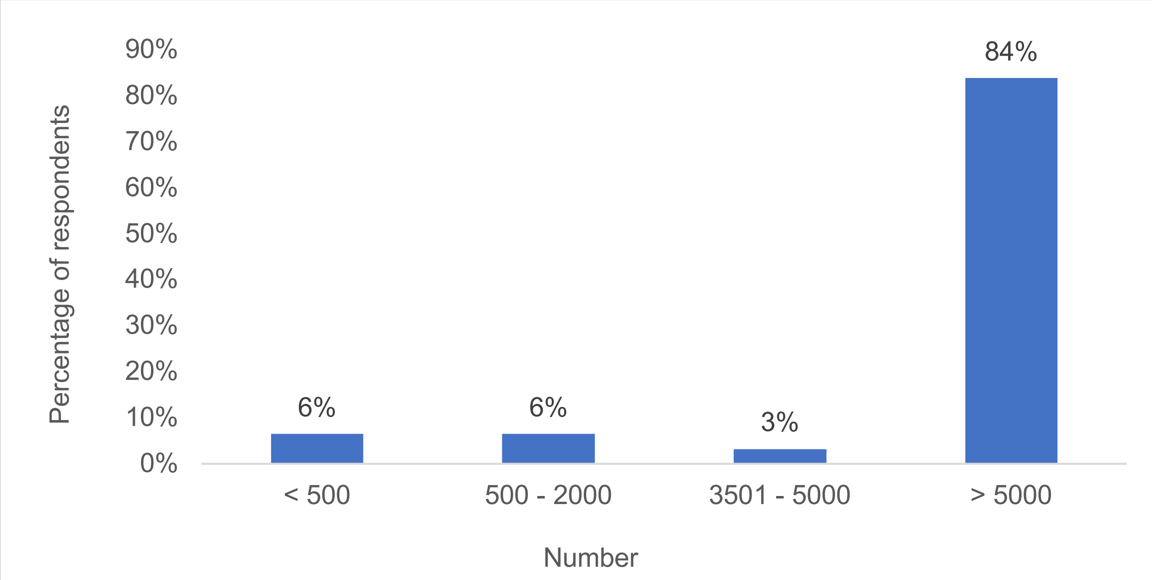

Figure 15: Number of employees

5.2.2 Customer experience sample

The profile of the sample for the customer experience study is shown in Table 14. most of the participants are female (57%), and fewer are male (43%). Regarding their level of education, almost half have a postgraduate qualification (40%), followed by those with a bachelor's degree (29%) and high school qualification (23%). Almost all of the respondents have a financial services product (95%). Of those, most have a banking product either as a standalone product or in combination with other financial products (93%), followed by almost half who also have at least an investment product (46%), and an insurance product (41%).

Regarding AI technologies, two-thirds of the respondents have previously used AI when engaging with financial services organisations (66%), while a quarter is not certain if they have previously used AI when engaging with financial services products (23%). Biometrics (53%) have been used, and chatbots or virtual assistants (43%) when engaging with financial services products and services. Regarding the frequency of AI usage when interacting with financial services, just more than a quarter use AI sometimes (28%), followed by those that often use (26%), rarely use (21%), always use (16%), and never use (9%).

Table 14: Respondents' profile for the customer experience data

Variable	Option	Frequency	Percentage
Gender	Male	174	43%
	Female	233	57%
Level of education	High school	94	23%
	Diploma	26	6%
	Bachelor	118	29%
	Postgraduate	163	40%
	Other	6	1%
Occupation	Employed	168	41%
	Self-Employed	21	5%
	Student	211	52%
	Unemployed	7	2%
Do you own any financial products (bank account, loans, insurance, investments, etc.)?	Yes	388	95%
	No	19	5%
Type of financial products owned[1]	Banking	377*	93%
	Investment	187*	46%
	Insurance	165*	41%
	Other	21	5%
Have you used any AI technologies as part of your engagement with the financial services organisation?	Yes	269	66%
	No	43	11%
	I am not sure	95	23%
AI technology used[2]	Chatbot/Virtual assistant	194**	48%
	Voice assistant	85**	21%
	Biometrics	215**	53%
	Other	32**	8%
	I am not sure	86**	21%
How frequently do you use AI technology?	Always	65	16%
	Often	107	26%
	Sometimes	113	28%
	Rarely	84	21%
	Never	38	9%

[1] * The total number of respondents that own the respective banking product as a standalone product or in combination with other financial products
[2] The total number of respondents that have used the respective AI technology either by itself or in combination with other AI technologies

5.3 Discussion pertaining to hypotheses

5.3.1 Discussion of AI adoption hypotheses

H1a. *There is a positive relationship between compatibility and AI adoption.*

The results show that hypothesis H1a was not supported as the path coefficient was less than zero; however, the result was insignificant because the *p-value* (0.383) was greater than 0.05. This result implies that the observed negative relationship between compatibility and AI adoption might not exist in the larger population. Therefore, based on these results, there is insufficient evidence to conclude that the observed relationship between compatibility and AI adoption exists. Compatibility remains questionable in the South African environment as many organisations do not have the quality of infrastructure to support the adoption of artificial intelligence.

In this study, participants are found to care about the compatibility of AI with the current software and hardware environment, compatibility of AI with infrastructure and compatibility of AI with computerised resources. This finding differs from previous research findings on AI adoption (Chang et al., 2006; Chen, 2019; Chong et al., 2009; Oliveira et al., 2014), which found compatibility strongly influenced AI adoption.

H1b. *There is a positive relationship between relative advantage and AI adoption.*

The results show that relative advantage (B = 0.121, *p-value* = 0.185) had a positive but insignificant effect on AI adoption. In this research, participants were found to care about improved employee productivity resulting from using AI applications, improving customer service, better utilisation of IT resources, and promotion of flexibility and integration. Given the high level of competition amongst the South African financial services organisations, they have to provide a great personalised experience to their customers or risk losing customers to competitors. Therefore, perceived benefits of AI adoption are seen to have some level of influence on the organisation's decision to adopt AI. The positive relationship between relative advantage and AI adoption is in line with previous research findings (AlSheibani et al., 2018; Chen, 2019; Ifinedo, 2005). Ifinedo (2005) found a relative advantage significantly impacts the intention to adopt robotic technology.

H1c. *There is a negative relationship between complexity and AI adoption.*

The results show that complexity (B = -0.245, *p-value* = 0.022) had a negative and significant effect on AI adoption. This result means that as the level of complexity associated with AI increases, the intention to adopt AI reduces. This study found that the application of AI costs associated with AI applications and migration, and the time it takes to innovate using AI, are strong indicators in the adoption decision. Some organisations may not have the required infrastructure and skills to develop and integrate AI applications as AI is still emerging. Instead, a huge amount of money may be required to build AI capabilities, prolonging operationalisation time. These are important considerations for financial services organisations, particularly when competing. These findings align with previous research that found complexity to be an inhibitor to technology adoption (Chen, 2019; Chong et al., 2009; Thong, 1999).

H2a. *There is a positive relationship between managerial support and AI adoption.*

The results show that managerial support (B = 0.218, *p-value* = 0.179) had a positive but insignificant effect on AI adoption. Therefore, there is insufficient evidence for concluding that a relationship between managerial support and AI adoption exists. In this study, respondents believe that top management must be willing to take the risks involved in AI adoption, exploit new technologies before competitors do, leverage new technologies as a strategic core competence, and use AI to increase business performance. The positive relationship between managerial support and AI adoption is in line with findings from previous research (Chen, 2019; Ifinedo, 2005; Mariemuthu, 2019).

H2b. *There is a positive relationship between technical capabilities and AI adoption*

Technical capabilities have a positive and significant impact (B = 0.358, *p-value* = 0.017) on AI adoption. Strong technical capabilities reduce integration complexity and enable the IT division to deploy AI technologies quickly and efficiently (Chen, 2019). Organisations with undeveloped technology infrastructure and low technical competencies may struggle to adopt new AI technologies due to a lack of skills and knowledge to integrate and extract value from these new technologies. Key indicators for AI adoption identified by respondents are standardised IT innovation processes, seamless integration of AI with existing IT infrastructure, IT strategies that align with business goals, and secured IT systems. This finding aligns with previous research (Aboelmaged, 2014; Mariemuthu, 2019). Mariemuthu (2019) found that the availability of highly developed IT infrastructure positively influences AI adoption.

H3a. *There is a positive relationship between managerial capabilities and the compatibility of AI*

H3b. *There is a positive relationship between managerial capabilities and the relative advantage of AI.*

H3c*. There is a negative relationship between managerial capabilities and the complexity of AI.*

H3d. *There is a positive relationship between managerial capabilities and managerial support.*

H3e*. There is a positive relationship between managerial capabilities and technical capabilities.*

The results show that managerial capabilities have a positive and significant effect (B = 0.371, *p-value* = 0.003) on compatibility of AI (**H3a**), a positive and significant effect on (B = 0.494, *p-value* = 0.003) relative advantage of AI (**H3b**), negative and significant effect (B = -0.259, *p-value* = 0.047) on complexity of AI (**H3c**), a positive and significant effect (B = 0.379, *p-value* = 0.017) on managerial support (**H3d**), and a positive and significant effect (B = 0.440, *p-value* = 0.000) on technical capabilities (**H3e**). According to Deloitte (2021), for organisations to adopt AI successfully, top managers must drive the culture of experimentation and innovation, access the necessary resources, and identify champions to drive change. Deloitte further posits that strategic training for executives and broader empowerment of users can reduce fears that AI deployment will reduce jobs that would otherwise reduce appetite for adoption. Top managers must ensure that AI solutions align with company values and consider broader ethical boundaries of AI to ensure AI use is in accordance with the laws and regulations.

Although there is a positive relationship between managerial capabilities and organisational capabilities and innovation characteristics, managerial capabilities do not influence AI adoption directly. Managerial capability influences AI adoption by enabling the organisation's technical capabilities and reducing complexities related to AI adoption. This result is in line with previous research findings (Chen, 2019; Ifinedo, 2005; Mariemuthu, 2019).

H4a. *There is positive relationship between government involvement and AI adoption*

The results show that government involvement (B = 0.024, *p-value* = 0.828) had a positive but insignificant effect on AI adoption. This result means there is insufficient evidence to conclude that a relationship between government involvement and AI adoption exists. Therefore, government involvement plays a very small or no role in AI adoption.

In this research, the following were identified as important indicators for government involvement in AI adoption:

- Clear and stable government policies
- Good relationship maintained with local authorities
- Government support in innovation and provision of relevant information.

The government is usually very slow to respond or get involved in new technologies within the South African context. An example of this is the government's response to cloud technologies. While cloud technology has been available for several years, a draft national policy on data and cloud computing was only issued in Apr 2021 (DCDT, 2021). Policy uncertainty is also a general challenge in South Africa, leading to the private sector championing the majority of the technology innovation with little to no government involvement. Previous studies found government involvement to significantly affect AI adoption (Borgman et al., 2013; Chen, 2019; Furst et al., 1998; Mariemuthu, 2019).

H4b. *There is a positive relationship between competitive pressure and AI adoption.*
The results show that competitive pressure (B = 0.197, *p-value* = 0.084) had a positive but insignificant effect on AI adoption. This result implies that competitive pressure plays a small to no role in AI adoption.

In this research, the following were identified as important indicators for competitive pressure in the South African financial services industry:

- The significant increase in the rate of innovation of new products and services
- Tough price competition
- Tough competition on product and service quality

Previous research found competitive pressure to have a significant influence on IT adoption. Mudzana and Kotze (2015) found that competitive pressure was an important determinant of business intelligence adoption in South Africa. However, other studies have found that competitive pressure does not play a role in technology adoption decisions (Chen, 2019; Mariemuthu, 2019).

H4c. *There is a positive relationship between market uncertainty and AI adoption.*
There was no valid construct for market uncertainty, and therefore it was removed from the final model.

H4d. *There is a positive relationship between vendor partnership and AI adoption.*
The results show that vendor partnership (B = 0.219, *p-value* = 0.075) had a positive but insignificant effect on AI adoption. This result means the presence of technology partners has an insignificant influence on the decision to adopt AI, but rather the presence of internal strong technical capabilities to drive and support the new technologies (as supported by H2b). While the presence of technical partners may accelerate the implementation of new technologies, this may not lead to actual adoption and acceptance of that technology within the organisation due to other internal factors such as culture.

In this research, the following were identified as important indicators for vendor partnership as it relates to AI adoption:

- Ease of obtaining reliable services from IT vendor partners
- Trustworthy technology partners
- Close relationship with vendors and technology partners
- Knowledgeable vendors and partners about AI technologies.

Previous studies on AI adoption have found a positive relationship between vendor partnership and AI adoption (Chen, 2019; Oliveira & Martins, 2011). Chen (2019) found that vendor partnership is a significant facilitator for AI adoption in that some organisations do not have essential AI competencies in-house.

5.3.2 Discussion of customer experience hypotheses

H5: *Perceived ease of use has a positive impact on customer experience.*

The results show that perceived ease of use (B = 0.417, *p-value* = 0.000) had a positive and significant effect on customer experience.

The components of perceived ease of use include:

- AI-powered applications (e.g. chatbots, virtual assistants, etc.) are easy to use
- It is easy for me to become skilful at AI-powered applications
- I find AI-powered applications to be flexible to interact with
- My interaction with AI-powered applications is clear and understandable
- Using financial products is easy if supported by AI.

In this study, respondents are found to care about the ease of learning and ease of mastery and skilful use of AI-powered applications and financial products as important indicators as to what makes AI-powered financial services applications easy to use. The hypothesis testing results show that perceived ease of use strongly influences user satisfaction in the context of AI-application usage. This finding aligns with previous research findings on user satisfaction (Childers et al., 2001; Rod et al., 2009; Sun et al., 2008). Childers et al. (2001) found that retailers with websites that are clear and understandable, helpful to customers when searching for items, and require less effort result in perceived ease of use and provide enjoyment to shoppers.

H6: *Perceived usefulness has a positive impact on customer experience.*

The results show that perceived usefulness (B = 0.231, *p-value* = 0.000) had a positive and significant effect on customer experience.

The components of perceived use usefulness include:

- The use of AI in financial services allows me to find the best products
- The use of AI in financial services is useful to me
- The use of AI in financial services allows me to get a personalised experience
- The use of AI in financial services helps me access financial information more quickly
- The use of AI in financial services saves time for me.

When searching for the best financial products and when interacting with AI-powered financial services applications and products, respondents care about a personalised experience, quick access to information, and time-saving. Thus, the perceived usefulness of the AI-powered applications and products strongly influences the overall user experience and their intentions to continue using these technologies. Previous studies found perceived usefulness as an important measure of customer satisfaction (Maryanto & Kaihatu, 2021; Rod et al., 2009; Sun et al., 2008).

5.4 Chapter summary

This chapter began by looking at the demographic profiles of respondents for both the AI-adoption factor instrument and the customer experience instrument. This demographic analysis was followed by a discussion of the results of hypotheses testing for AI adoption and customer experience studies. The results show that for AI-adoption factors, only complexity and technical capabilities significantly influenced AI adoption, with managerial capabilities indirectly influencing the adoption of AI in South African financial services. All other latent factors had statistically insignificant results.

For the customer experience study, the results show that both perceived ease of use and perceived usefulness are important indicators of how customers experience AI applications of financial services organisations.

CHAPTER 6. CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

Chapter 6 discusses the conclusions of both the AI-adoption study and the customer experience study, makes recommendations to South African financial services organisations, and proposes areas for future research.

6.2 Conclusion regarding AI adoption

Artificial intelligence has the ability to advance financial services by transforming customer service experience through personalised products and services, allowing for improved efficiencies, and risk management (Linklaters, 2019). While factors that enable the successful implementation of AI in organisations were previously studied, these studies are still in the early stages. Therefore, the objective of this study was to investigate the success factors for AI adoption by South African financial services companies, using an integration of the DOI theory and TOE framework. This study also aimed to understand the relative effect of factors affecting AI adoption in financial services in South Africa.

The study was administered using an online survey targeting employees of South African financial services organisations. A total of 70 responses were received, of which eight were incomplete and were deleted, resulting in the final sample of 62 respondents. The results show that for innovation characteristics, only complexity has a significant influence on AI adoption. The other two innovation characteristics (relative advantage and compatibility) have statistically insignificant results. Therefore, the results are inconclusive of the role played by relative advantage and compatibility in

AI adoption. There is a possibility that these factors may still influence AI adoption in other situations, for example, in different industries or countries.

For organisational capability, technical capabilities significantly influenced AI adoption, while managerial support had statistically insignificant results on AI adoption. However, managerial capabilities greatly influenced organisational capabilities and innovation characteristics, thus indirectly influencing AI adoption.

Lastly, for external environmental factors, government involvement, competitive pressure, and vendor partnerships all had statistically significant results for AI adoption. There was also no valid construct for market uncertainty, and therefore it was removed from the final model. Government regulations have not kept pace with new market-related technologies such as AI.

6.3 Conclusion regarding customer experience

The use of AI technologies in organisations has fundamentally changed how organisations interact with their customers. Financial services organisations use AI applications such as chatbots to provide financial advice and create a better financial experience for customers. Therefore, the objective of this study was to use TAM to understand how customers experience AI applications after adoption by financial services products. An online survey was administered to South African financial services customers, resulting in 407 valid (complete) responses.

The results showed that both perceived ease of use and perceived usefulness had a significant influence on how customers experience AI-powered applications and services in financial services organisations. The results show that customers value the ease of learning and interacting with the AI applications and getting a personalised experience that enables them to meet their financial needs quicker.

Overall, financial services customers perceived their interactions with AI-powered applications to be educational, exciting, memorable, entertaining, and they get a sense of comfort from using these AI-powered applications.

6.4 Recommendations for AI adoption

When adopting AI in their organisations, the leadership of financial services organisations should consider the costs associated with AI applications, the time taken to innovate using AI, and the application of AI. A clear business case should be defined at the outset, with a clear definition of the problem statement, a solution design, and costs to help reduce the complexities associated with AI adoption.

Financial services organisations should develop appropriate technical capabilities, including skills, suitable hardware and software, and defined IT processes and strategies, when planning to adopt AI. Financial services organisations should also develop strong managerial capabilities to help identify real business challenges that AI can help solve and ensure the appropriate use of AI solutions relative to company value and regulations.

While government regulations have not kept pace with new technologies such as AI in the market, financial services organisations still need to ensure strong internal governance when adopting AI and build internal technical capabilities to drive the implementation of AI. It is also worth noting that, while the environmental factors have an insignificant influence on AI adoption in this study, there is a possibility that these factors may still influence AI adoption in other situations.

6.5 Recommendations for customer experience

Financial services organisations should ensure an optimal level of ease of use and prioritise utilitarian benefits when designing and adopting AI applications. Financial services organisations also need to ensure that services are available to their customers at any time and that customers are provided with relevant information throughout their engagements with the AI applications.

6.6 Suggestions for further research

The focus of this study was on the South African financial services organisations. Therefore, this study's AI-adoption factors only reflect situations in one industry and one nation. Investigating AI-adoption factors in a different sector could be beneficial to enhance the generalisation of the findings.

This study uses limited dimensions of the DOI theory and TOE framework. Future research could incorporate additional dimensions, such as the organisational slack and size, to investigate AI-adoption factors. Future research could also look at a different framework, such as institutional theory, to understand how an organisation adopts AI.

The customer experience study uses TAM, focusing on perceived ease of use and perceived usefulness, to understand how customers experience AI after adoption by financial services organisations. Future research should use customer experience frameworks to understand how customers receive AI applications, focusing on additional aspects of customer experience, such as cognitive, emotional, physical and sensorial, and social elements.

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APPENDIX A: PARTICIPANT INFORMATION SHEET

To: Financial services employees

Adoption of artificial intelligence – in financial services in South Africa

Dear Participant,

My name is Anele Qwabaza. I am completing my Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. In my journey, I am required to complete a research project, for which I have chosen the financial services sector. I am conducting research on the adoption of artificial intelligence by South African financial services organisations under the supervision of Dr Manessah Alagbaoso.

I humbly request your assistance in enabling me to complete my task by taking part in this survey. Attached is a questionnaire that should take no longer than 25 minutes to complete. You are not required to provide your name, so your response is completely anonymous, and confidentiality is guaranteed. You are required to provide some demographic information please, which is used purely to establish patterns between various demographies.

The first part of the survey captures some demographic data. Please tick the applicable options. The second part of the survey comprises 46 statements. Please indicate the extent to which you agree with each statement by ticking in the appropriate box. Your participation is completely voluntary and involves no risk, penalty, or loss of benefits whether or not you participate. You may withdraw from the survey at any stage. Submission of the questionnaire will be taken as your consent to participate.

Thanking you in advance. Please feel free to contact me should you have any queries in this regard at anele.qwabaza1@students.wits.ac.za or on 072 535 0845.

Regards,

Anele Qwabaza

To: External customers of financial services organisations

Dear Participant,

My name is Anele Qwabaza. I am completing my Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. In my journey, I am required to complete a research project, for which I have chosen the financial services sector. I am conducting research on how customers experience Artificial intelligence applications after adoption by South African financial services organisations under the supervision of Dr Manessah Alagbaoso.

I humbly request your assistance in enabling me to complete my task by taking part in this survey. Attached is a questionnaire that should take no longer than 20 minutes to complete. You are not required to provide your name, so your response is completely anonymous, and confidentiality is guaranteed. You are required to please provide some demographic information, which is used purely to establish patterns between various demographies.

The first part of the survey captures some demographic data. Please tick the applicable options. The second part of the survey comprises 23 statements. Please indicate the extent to which you agree with each statement by ticking in the appropriate box. Your participation is completely voluntary and involves no risk, penalty, or loss of benefits whether or not you participate. You may withdraw from the survey at any stage. Submission of the questionnaire will be taken as your consent to participate.

Thanking you in advance. Please feel free to contact me should you have any queries in this regard at anele.qwabaza1@students.wits.ac.za or on 072 535 0845.

Regards,

Anele Qwabaza

APPENDIX B: ETHICS CLEARANCE CERTIFICATE

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

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

Ethics Clearance Certificate

Ethics protocol number: WBS/DB0314719J/917

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

Project title	The adoption of artificial intelligence in the financial service industry in South Africa
Investigator / Researcher	Mr Anele Qwabaza
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	2021-09-23
Expiry date	Date of submission of the project report
Chairperson	Prof Anthony Stacey ☎ +27 11 717 3587 +27 82 880 4531 anthony.stacey@wits.ac.za

Declaration by Researcher

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

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

Signature

27 Sep 2021
Date:

APPENDIX C: RESEARCH INSTRUMENT

AI Adoption

#	Background Information							
1	Current role							
2	Age	< 30	31- 40	41- 50	51-60	> 60		
3	Level of education	High school	Diploma	Bachelor	Post Graduate	Other		
4	How long have you been in your current role?	0-1 year	2-4 years	5-7 years	8-10 years	> 10 years		
5	How long have you been in your organisation?	0-1 year	2-4 years	5-7 years	8-10 years	> 10 years		
6	Which of the following best describe your organisation?	Banking	Wealth management	Insurance	Advisory	Mutual Funds	Other	
7	Number of employees	< 500	500 - 2000	2001 - 3500	3501 - 5000	> 5000		
	AI Adoption Factors							
	Government involvement (GI)							
8	Clear and stable government policies are beneficial for business operations	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
9	We should maintain a good relationship with the local government	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
10	The government support and help are very important for us to innovate	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
11	The government can supply related information	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Market uncertainty (MU)							
12	There is a trend in our industry to utilise more AI technologies for business development and applications.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
13	Only innovative technologies can help our company to provide perfect products and services to meet the growing personalised needs of consumers.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
14	AI has broad application prospects in our industry.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
15	AI can help our company to gain competitiveness.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Competitive pressure (CP)							
16	The rate of innovation of new operating processes and new products or services in our industry has increased dramatically.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
17	An industry move to utilise AI technologies would put pressure on our company to do the same.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
18	There is tough price competition in our industry.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree

19	There is tough competition on product/service quality in our industry.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Vendor partnership (VP)							
20	We have had no difficulty in obtaining assistance or reliable services from our vendors/partners.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
21	Our technology partners are trustworthy.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
22	We have very close relationships with vendors/technology partners.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
23	Our vendors/partners are knowledgeable about AI technologies.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Managerial capability (MC)							
24	We have clear goals and objectives to adopt AI technology innovation.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
25	Inter-department cooperation is very important to adopt AI technology innovation.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
26	Inter-department communication is very important to adopt AI technology innovation.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
27	Formal education and training programs can be developed to include all classes of users ranging from managers to shop floor controllers.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Managerial support (MS)							
28	Managers are willing to take risks involved in the adoption of AI.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
29	Our managers have the ability to exploit new technologies before our competitors.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
30	Our managers have the ability to leverage IT new technologies as a strategic core competence.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
31	Our managers have a strong understanding of how AI technology can be used to increase business performance.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
32	Senior managers explicitly demonstrate to support the adoption of AI.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Technical capability (TC)							
33	We have a standardised process for IT innovation.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
34	We can quickly integrate new AI technologies into our existing infrastructure.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
35	Our IT strategies support our business strategies.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
36	We have suitable hardware/software to protect the security and privacy of our systems and networks.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Compatibility ©							
37	AI applications are compatible with our current software environment.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
38	AI applications are compatible with our current hardware environment.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree

39	AI application is compatible with our infrastructure.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
40	AI application is compatible with computerised data resources.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Relative advantage (RA)							
41	AI applications can get higher employee productivity.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
42	AI applications can improve customer service.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
43	AI applications can better utilise IT resources.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
44	AI applications can promote flexibility and integration.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Complexity (CX)							
45	Adopting AI innovation lacks application maturity.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
46	There has been a high cost for AI application and migration.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
47	Adopting AI innovation is time-consuming.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
48	Inappropriate staffing and personnel shortfalls are a big issue for adopting AI innovation.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	AI adoption							
49	A timely AI technical implementation and application migration plan has been developed.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
50	The plan has already been endorsed by managers.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
51	A financial budget and a migration schedule have been approved.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
52	Our customers highly accept new products and services using AI innovations.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
53	We get improvement in the competitive position after adopting AI innovation.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree

Customer experience

#	Background Information							
1	Age	< 30	31-40	41-50	51-60	> 60		
2	Gender	Male	Female					
3	Level of education	High school	Diploma	Bachelor	Post Graduate	Other		
4	Occupation	Self-Employed	Student	Employed	Unemployed			
5	Do you have any financial products?	Yes	No					
6	What type of financial products do you own – please select the applicable options	Banking	Investment	Insurance	Other			
7	Have you use any AI technologies as part of your engagement with the financial services organisation?	Yes	No					
8	Which AI technology did you use	Chatbot | virtual assistant	Voice Assistant	Biometrics	Other			
9	How frequent do you use the AI technology	Always	Often	Sometimes	Rarely	Never		
	AI Adoption Factors							
	Perceived Usefulness							
10	The use of AI in financial services allows me to find the best products.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
11	The use of AI in financial services is useful to me.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
12	The use of AI in financial services saves allows me to get a personalised experience.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
13	The use of AI in financial services helps me access financial information more quickly.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
14	The use of AI in financial services saves time for me.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Perceived Ease of Use							
15	AI-powered applications (e.g., chatbots, virtual assistants etc.) are easy to use.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
16	It is easy for me to become skilful at AI-powered applications.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
17	I find AI-powered applications to be flexible to interact with	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
18	My interaction with AI-powered applications is clear and understandable.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
19	Using financial products is easy if supported by AI.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
	Attitude towards Using							
20	Using AI in financial services is a good idea.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
21	Using AI in financial services is a wise idea.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
22	I think it is valuable to use AI in financial services.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
23	I think it is a trend to use AI in financial services.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
24	I am positive about AI-powered applications in financial services.	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree

	User Satisfactions							
25	It is more fun, enjoyable when AI helps me to find the best-suited products.	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
26	I believe that using AI has improved the quality of the financial service industry.	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
27	I am completely satisfied with the use of AI in financial services.	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
	Overall Customer Experience							
28	My overall experience from using AI-powered applications in financial services has been:							
29	· Educational	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
30	· Exciting	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
31	· Memorable	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
32	· Entertaining	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
33	· Sense of comfort	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**

APPENDIX D: RESULTS

AI adoption validity

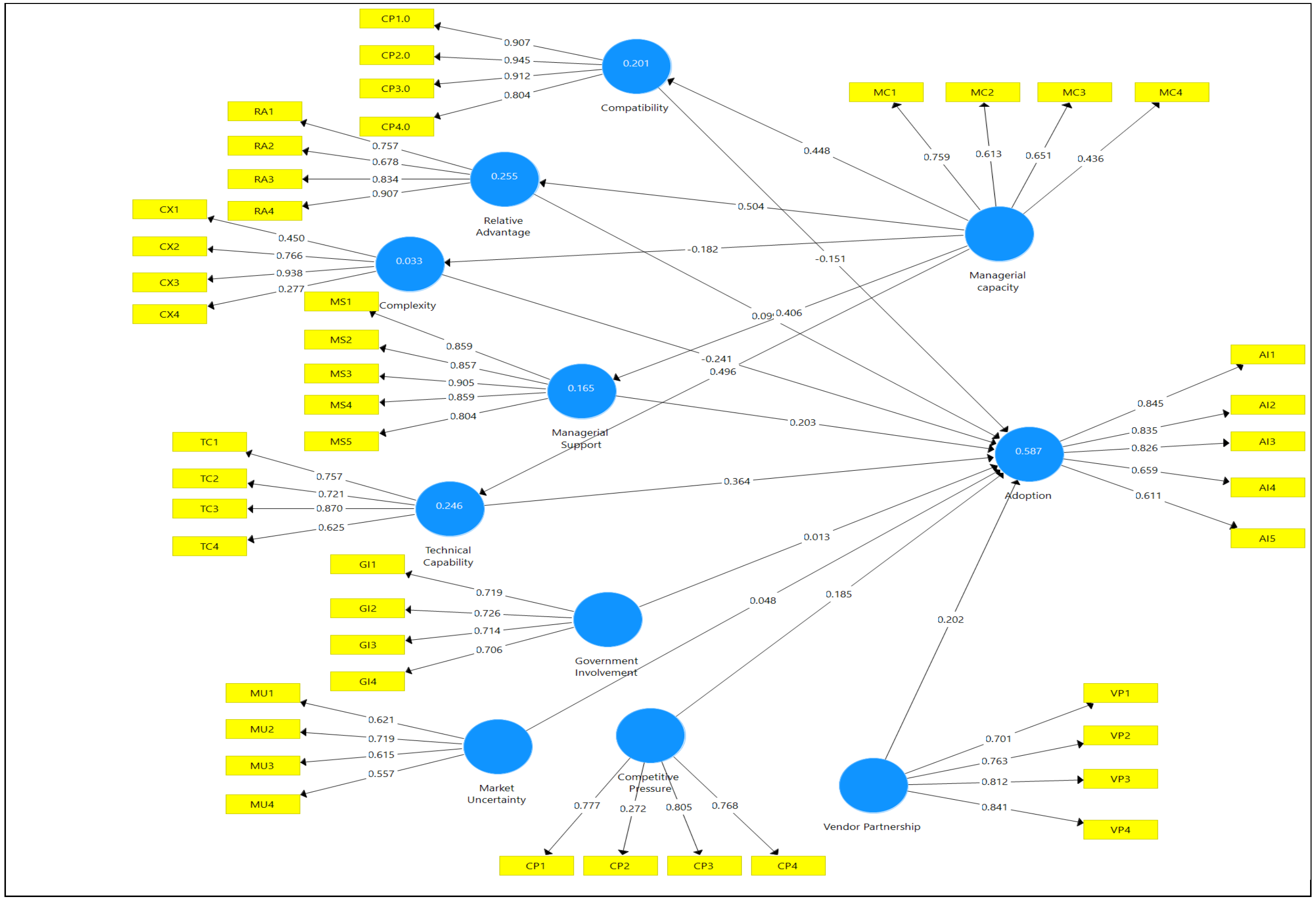

Figure 16: CFA: Hypothesised AI adoption mode

	Cronbach's alpha	Rho_a	Composite reliability	Average variance extracted (AVE)
Adoption	0.813	0.824	0.872	0.580
Compatibility	0.915	0.923	0.940	0.799
Competitive pressure	0.581	0.682	0.767	0.479
Complexity	0.678	0.971	0.724	0.436
Government involvement	0.687	0.690	0.808	0.513
Managerial support	0.910	0.914	0.933	0.735
Managerial capacity	0.544	0.526	0.713	0.391
Market uncertainty	0.531	0.523	0.724	0.398
Relative advantage	0.807	0.826	0.874	0.638
Technical capability	0.734	0.768	0.834	0.560
Vendor partnership	0.792	0.849	0.862	0.610

Table 15: Construct reliability and validity: Hypothesised model

	Adoption	Compatibility	Competitive pressure	Complexity	Government involvement	Managerial support	Managerial capacity	Market uncertainty	Relative advantage	Technical capability	Vendor partnership
Adoption	0.762										
Compatibility	0.437	0.894									
Competitive pressure	0.501	0.258	0.692								
Complexity	-0.272	-0.052	-0.110	0.661							
Government involvement	0.191	0.234	0.409	0.135	0.716						
Managerial support	0.547	0.666	0.381	0.098	0.300	0.858					
Managerial capacity	0.498	0.448	0.312	-0.182	0.185	0.406	0.626				
Market uncertainty	0.367	0.353	0.285	-0.085	0.279	0.306	0.433	0.631			
Relative advantage	0.348	0.314	0.145	-0.036	0.044	0.268	0.504	0.382	0.799		
Technical capability	0.613	0.701	0.374	-0.034	0.224	0.702	0.496	0.316	0.372	0.749	
Vendor partnership	0.523	0.427	0.403	-0.099	0.045	0.479	0.443	0.398	0.257	0.395	0.781

Table 16: Fornell-Larcker criterion: Hypothesised model

	Adoption	Compatibility	Competitive pressure	Complexity	Government involvement	Managerial support	Managerial capacity	Market uncertainty	Relative advantage	Technical capability	Vendor partnership
AI1	0.845	0.323	0.459	-0.178	0.115	0.568	0.410	0.342	0.244	0.506	0.485
AI2	0.835	0.362	0.360	-0.113	0.055	0.534	0.273	0.218	0.244	0.486	0.353
AI3	0.826	0.338	0.406	-0.243	0.126	0.401	0.431	0.219	0.232	0.541	0.444
AI4	0.659	0.387	0.310	-0.362	0.168	0.230	0.347	0.274	0.319	0.386	0.304
AI5	0.611	0.260	0.354	-0.155	0.280	0.303	0.433	0.345	0.300	0.398	0.379
CP1.0	0.457	0.907	0.248	-0.052	0.141	0.645	0.390	0.338	0.188	0.609	0.463
CP2.0	0.429	0.945	0.303	-0.036	0.168	0.641	0.430	0.281	0.284	0.599	0.495
CP3.0	0.314	0.912	0.182	-0.031	0.253	0.534	0.411	0.356	0.386	0.621	0.315
CP4.0	0.348	0.804	0.174	-0.066	0.298	0.548	0.367	0.292	0.280	0.688	0.222
CP1	0.440	0.331	0.777	-0.090	0.384	0.347	0.428	0.364	0.216	0.423	0.352
CP2	0.177	0.186	0.272	-0.098	0.042	0.028	0.437	0.235	0.459	0.198	0.268
CP3	0.374	0.150	0.805	0.052	0.345	0.367	0.090	0.125	-0.027	0.217	0.285
CP4	0.330	0.027	0.768	-0.200	0.246	0.196	-0.012	0.063	-0.088	0.157	0.219
CX1	0.014	-0.060	0.306	0.450	0.151	0.129	-0.121	-0.077	-0.060	-0.007	0.147
CX2	-0.104	-0.042	-0.007	0.766	0.255	0.160	-0.133	0.017	0.040	0.027	-0.082
CX3	-0.317	-0.038	-0.182	0.938	0.044	0.042	-0.163	-0.113	-0.065	-0.051	-0.098
CX4	0.023	0.039	0.125	0.277	0.057	0.051	0.013	-0.061	-0.112	0.078	0.270
GI1	0.164	0.017	0.302	0.177	0.719	0.209	0.201	0.107	0.084	0.075	0.017
GI2	0.123	0.136	0.201	0.022	0.726	0.229	0.275	0.359	0.031	0.186	-0.008
GI3	0.120	0.119	0.428	0.027	0.714	0.153	0.002	0.123	-0.073	0.162	0.021
GI4	0.131	0.433	0.244	0.128	0.706	0.266	0.032	0.239	0.062	0.244	0.099
MC1	0.535	0.451	0.404	-0.295	0.079	0.505	0.759	0.304	0.291	0.481	0.571
MC2	0.196	0.055	-0.023	-0.117	-0.033	-0.002	0.613	0.200	0.438	0.124	0.050
MC3	0.254	0.091	0.015	-0.046	0.012	0.056	0.651	0.188	0.443	0.175	0.145
MC4	0.050	0.323	0.138	0.174	0.416	0.166	0.436	0.374	0.202	0.281	0.025
MS1	0.544	0.566	0.377	0.015	0.214	0.859	0.315	0.229	0.177	0.623	0.355
MS2	0.463	0.533	0.276	0.113	0.265	0.857	0.330	0.069	0.190	0.584	0.310
MS3	0.445	0.621	0.278	0.027	0.370	0.905	0.366	0.246	0.223	0.640	0.412
MS4	0.487	0.542	0.370	0.065	0.205	0.859	0.405	0.471	0.325	0.571	0.573
MS5	0.392	0.603	0.324	0.225	0.244	0.804	0.321	0.279	0.227	0.593	0.393
MU1	0.221	0.280	0.093	-0.013	0.262	0.295	0.353	0.621	0.038	0.347	0.252
MU2	0.322	0.237	0.188	-0.109	0.072	0.211	0.146	0.719	0.327	0.098	0.385
MU3	0.158	0.083	0.236	-0.096	0.200	0.043	0.422	0.615	0.248	0.136	0.085
MU4	0.167	0.274	0.247	0.033	0.260	0.184	0.301	0.557	0.365	0.280	0.174
RA1	0.347	0.270	0.123	-0.072	0.029	0.302	0.418	0.280	0.757	0.224	0.383
RA2	0.202	0.165	0.020	-0.008	0.078	0.189	0.340	0.339	0.678	0.274	0.091
RA3	0.197	0.236	0.122	0.070	-0.015	0.115	0.382	0.312	0.834	0.302	0.072
RA4	0.330	0.307	0.172	-0.076	0.051	0.224	0.454	0.305	0.907	0.383	0.217
TC1	0.527	0.393	0.517	-0.014	0.277	0.467	0.338	0.181	0.169	0.757	0.232
TC2	0.395	0.554	0.060	-0.239	0.056	0.466	0.332	0.300	0.210	0.721	0.185
TC3	0.570	0.571	0.289	-0.033	0.109	0.627	0.453	0.254	0.399	0.870	0.306

TC4	0.294	0.632	0.211	0.212	0.252	0.547	0.358	0.228	0.331	0.625	0.512
VP1	0.326	0.250	0.288	-0.108	0.044	0.304	0.133	0.359	0.083	0.211	0.701
VP2	0.337	0.300	0.186	-0.046	-0.074	0.468	0.275	0.275	0.159	0.326	0.763
VP3	0.322	0.320	0.192	0.121	-0.003	0.315	0.282	0.236	0.196	0.250	0.812
VP4	0.559	0.420	0.488	-0.194	0.118	0.403	0.559	0.354	0.302	0.396	0.841

Table 17: Outer loadings – AI adoption hypothesised model

	Customer experience	Perceived ease of use	Perceived usefulness
OE_1	0.763	0.428	0.390
OE_2	0.890	0.507	0.465
OE_3	0.831	0.466	0.391
OE_4	0.826	0.401	0.334
OE_5	0.821	0.530	0.484
PEOU1	0.360	0.768	0.470
PEOU2	0.300	0.697	0.397
PEOU3	0.497	0.825	0.545
PEOU4	0.477	0.838	0.506
PEOU5	0.540	0.808	0.632
PU1	0.435	0.494	0.792
PU2	0.424	0.575	0.868
PU3	0.481	0.569	0.844
PU4	0.387	0.579	0.857
PU5	0.376	0.544	0.827

Table 18: Cross loadings – customer experience sample