Research Article

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Factors Driving Artificial Intelligence Adoption in South Africa's Financial Services Sector

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Abstract

Incorporating digital technologies, particularly artificial intelligence, into financial services operations is imperative for achieving critical sustainable development goals (SDGs) through digital financial inclusion. This paper examines the drivers behind AI adoption in South Africa's financial services landscape, given its highly advanced financial sector and rapidly evolving digitisation trends. Drawing on the Technological-Organizational-Environmental (TOE) framework, the study investigates the factors influencing AI adoption through a comprehensive analysis of existing literature, a survey of financial services professionals and binary logistic regression. The results of binary logistic regression indicated that technological, organisational and environmental improvements significantly enhance the likelihood of AI adoption in South Africa's financial services sector. Specifically, access to technological infrastructure, organisational leadership support, and regulatory clarity emerge as key determinants of AI adoption. Overall, this study underscores the need for companies in the financial sector to encourage a culture that welcomes innovation and the integration of AI technology, as well as the need for policymakers to develop comprehensive and unambiguous legislative frameworks that control AI use in financial services.

Keywords: *artificial intelligence, financial services, South Africa, logit regression, TOE framework*

1. Introduction

Incorporating digital technologies into financial services operations is vital in achieving critical sustainable development goals (SDGs) through digital financial inclusion. This process enhances the accessibility of formal financial services for populations currently excluded from them (Peric, 2015). Biallas and O'Neill (2020) argued that within emerging markets, the financially excluded populace (which largely comprises small/micro businesses, women and youth) lack access to the standard identification documentation typically demanded by mainstream financial services providers. The emergence of Industry 4.0 tackles this problem by employing cyber-physical systems that possess autonomous decision-making abilities, incorporating artificial intelligence (AI). These technologies enable the provision of personalised solutions to address the wide range of challenges encountered by financial institutions' customers (Deloitte, 2018; Mhlanga & Moloi, 2020).

In recent times, technological innovation has become increasingly crucial for the evolution of financial services, adding value for financial institutions and their customers. AI offers banks the potential to offer innovative products, which have been a key focus in their marketing strategies for a long time (Furst et al., 1998). The uptake of online financial services, facilitated by mobile phones utilisation and AI technology, has occurred in upwards of eighty countries (Chu, 2018; WEF, 2020). As a result, millions of individuals who were previously excluded from financial services have been able to shift from relying solely on cash transactions to engaging in formal financial activities such as making online payments, transferring funds, accessing credit, saving money, and obtaining insurance (WEF, 2020). Furthermore, Gomber et al. (2017) averred that it has positively impacted the financial services delivered by financial institutions by enhancing their affordability and sustainability. As such, AI is primarily incorporated by financial institutions, leading to a remarkable enhancement in global financial inclusion (Bill & Melinda Gates Foundation, 2019). AI made this achievable by remedying the information asymmetry troubling traditional attempts at financial inclusion (Gomber et al., 2017).

The adoption of AI technologies by financial services providers was predictable, given the various advantages of AI. PricewaterhouseCoopers (PwC) forecasted the global GDP and the global economy to be boosted by approximately 26% and 15.7 trillion USD, respectively, by 2030, highlighting its significance in the current global business environment (PwC, 2024). It was also highlighted that adopting AI tools offers various benefits, such as streamlined and top-notch decision-making, improved operational efficiency and boosted productivity (Zhang et al., 2021). According to Ryll et al. (2020), AI has impacted financial institutions' performance through various technologies by enhancing their competitiveness through innovative products and services, improved operational efficiency and reduced lead time. Therefore, AI adoption in financial intermediation has markedly risen in recent decades. Nvidia (2023) reported that in 2022, about 91% of organisations in the sector invested in AI to propel essential customer services and business goals.

The purpose of this paper is to examine the factors driving AI adoption in South Africa's financial services landscape. South Africa presents an intriguing subject for discussing the drivers of AI adoption in the financial services landscape for some compelling reasons. The nation boasts a highly advanced financial sector with a well-established infrastructure, a top-tier banking system, and robust financial regulation. Moreover, the overall financial system development rate appears to be impressive. For example, in sub-Saharan Africa (SSA), the financial market in South Africa is the most developed (Phiri, 2015; Adusei, 2019). The nation's financial system is positioned within the best ten globally (Shahbaz et al., 2013; Adusei, 2019). Additionally, South Africa was ranked eighth following the WEF Global Competitiveness Survey for the 2015/2016 period, involving one hundred forty countries (Adusei, 2019). Besides, South Africa has a mature financial market that prioritises development and accounts for 40% of Africa's financial technology (fintech) revenue (Go-Globe, 2024). These attributes establish a solid groundwork for digital and fintech innovation to thrive.

Further to these attributes, the pace of digitisation and AI transition in South Africa has been described as the fastest in Africa. It has been reported that South Africa is at the forefront of AI-focused companies on the African continent (Figure 1). Moreover, it has been shown by a financial sector outlook study on South Africa that for over a decade, South Africa's largest banks have strategically emphasised the transition towards customer self-service through digitalisation and that the sector's accelerated digitalisation has resulted in a higher adoption rate of digital products (FCSA, 2024). For example, between 2018 and 2019, there was a 4-percentage-point increase in the proportion of individuals using banking apps and mobile banking, while retail stores have gained popularity as a distribution channel for basic transactions, as evidenced by Tyme Bank's partnerships with Pick 'n Pay and the Checkers Money Market (FCSA, 2024).

Moreover, there has been a significant increase in AI-powered FinTech innovations and mobile payment solutions in the country in recent years. Popular mobile payment platforms like 2checkout, Mobicred, Netcash, Ozow, PayFast, Payflex, Paygate, PayU, SnapScan, Stripe South Africa, Yoco and Zapper have emerged, offering users convenient and secure transaction methods[1]. Companies such as Capitec Bank and MTN Group have launched mobile banking platforms, enabling users to conduct financial transactions through their mobile devices. This has significantly increased financial accessibility, especially to the rural and underserved populace. This aligns with the assertion that FinTech has made significant strides, with the growing popularity of mobile banking and digital payment solutions addressing challenges in financial inclusion (PwC, 2017). Some of the implications of promoting AI-driven financial sector in South Africa could include enhanced access to credit facilities made possible by AI-driven algorithms for risk assessment, fraud detection and personalized financial services (Khrais, 2015). It could also bolster efficiency and cost reduction (PwC, 2020), enhanced customer experience (EY, 2019) and competitive advantage (KPMG, 2020).

Nevertheless, South Africa is a developing economy characterised by high levels of inequality, consistently listed among the most unequal countries globally (Stats SA, 2019). The country's income inequality is profound, with a disproportionately wide gap that adversely affects the vast majority (WID, 2019). This level of inequality has prevented the development of the financial system from enhancing the financial inclusion objective (Hassan & Meyer, 2020). Recent initiatives aimed at broadening financial inclusion in South Africa have seen some progress, but there is still much to do, especially regarding deepening financial inclusion through AI integration. According to a survey by FCSA (2024), about 20% of adults in South Africa do not possess a basic bank account (or approximately 30% if social grant beneficiaries are not included). The underbanked population also exists in addition to the unbanked population; 47% of those with bank accounts are thought not to utilise them to their full potential (FinScope, 2022). AI has huge potential to support financial inclusion in some ways: communicating in the mother tongue of customers, offering personalised services and financial education, saving customers from the hassle of visiting branches and waiting for an available banking consultant, and lowering the overheads associated with serving customers, thereby decreasing prices for them (Marrie et al., 2023).

Exploring the factors that propel AI adoption in South Africa's financial system is essential, especially given the widespread use of AI in financial services worldwide and the necessity of formulating an effective framework for deepening the level of AI adoption that would boost the attainment of the much-desired financial inclusion in the country. Despite the merits of implementing AI in financial services, research is scarce on the practical aspects of AI adoption. The few studies available have predominantly examined psychological factors and have overlooked the intricacies of practical contexts regarding AI adoption dynamics (for example, Atwal et al., 2021; Noonpakdee, 2020). For South Africa, in particular, the author is unaware of any prior research examining the factors influencing the uptake of AI in the country despite its flourishing state in the sector. Therefore, the study will contribute to the existing literature by identifying the operational drivers of AI adoption in South Africa's financial services sector, thereby charting the path towards deepening the pace of financial inclusion in the country.

[1] *https://portmoni.com/best-payment-gateway-south-africa/*

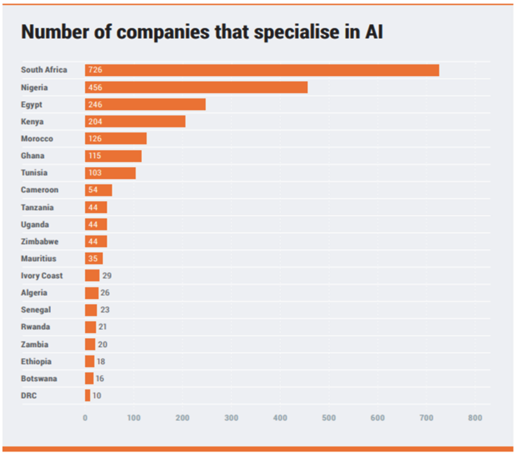


Figure 1: AI-focused companies in Africa by countries
Source: Alikhan (2023)

2. Literature review

Over the past two decades, there has been a significant increase in the integration of AI across industries, which has basically changed how businesses operate (Herrmann, 2023). The demand for artificial intelligence (AI) has increased due to the recent COVID-19 pandemic, which has forced organisations in the public and business sectors to give careful thought to integrating AI. The literature is filled with numerous enablers of AI adoption in financial services sector. Various researchers have highlighted many factors, which fall into different categories. The most prominent of these factors are those categorised as psychological and operational factors (Kumari et al., 2022). Some of the psychological enablers include social conventions and their impact, building confidence in the capabilities of AI, familiarity with using AI tools, desire to utilise AI, etc. (Atwal et al., 2021; Noonpakdee, 2020). On the other hand, the operational factors align with the aim of this study and fall within the ambit of the Technology-Organisation-Environment (TOE) framework upon which this study is predicated.

The study by world wide worx with SYSPRO revealed that AI is not being enthusiastically adopted by major organisations in South Africa, despite marketing claims to the contrary (Goldstuck, 2019). Specifically, the study found that just 13% of South African corporates now use AI, and 21% of the remaining companies intend to do so within the next 12 to 24 months. Slow adoption of innovative technologies has been attributed, among other factors to the risks involved (Oliveira et al., 2014).

AI is known to significantly impact many aspects across businesses due to its versatility (Taddy, 2019). Thus, it is no wonder that in the study by Harapko (2021), 63% of the examined organisations are investing more resources in AI and automation. According to Goodell et al. (2021), the financial services sector is not immune to the trend and is using AI to improve customer experience, reduce risks, and optimise operational efficiency. In fact, Biallas and O'Neill (2020) claimed that AI has been applied more widely in the financial sector than in many other sectors. In a recent survey, 77% of financial institutions predicted that artificial intelligence (AI) would be highly important for their businesses during the next two years (WEF, 2020). Additionally, McKinsey (2020) projected that AI might be worth $1 trillion within the banking industry. Since the 1980s and 1990s, scholarly publications have investigated and documented the many effects of AI on financial services delivery (Pau & Tan, 1996; Shap, 1987). Perspectives on several implications, possibilities, and concerns have been provided by the recent deluge of literature on this topic.

According to Wittmann and Lutfiju (2021), the use of RPA (Robotic, Cognitive robotic, AI) algorithms to automate important business activities has benefitted financial organisations. These RPA are primarily utilised in wealth management and retail banking as robo-advisors to enhance consumer services (Kruse et al., 2019). Their importance manifests in their capability to provide tax planning help, bank account opening services, insurance policy recommendations, investing advice, and a host of other crucial financial services. The primary benefit of implementing RPA services in retail banking is that it enables banks to provide state-of-the-art services, work around the clock, and enhance customer experiences all while boosting accuracy and efficiency (Villar & Khan, 2021). It is also often employed by insurance companies especially when pre-validating claims that have already been granted. Moreover, by implementing RPA, an insurance claims outsourcing and loss adjusting agency could process almost 3,000 claims documents each day with just four employees (Cranfield & White, 2016).

Trading, including equity and, more recently, foreign currency market trading, is another important domain in which AI has been used. According to Cohen (2022), because algorithms use a variety of real-time data sets to account for price variations and take into account market abnormalities, they have shown to be more efficient than human traders. Moreover, given their ability to quickly detect unanticipated market patterns, AI-models can provide human traders with superior trading recommendations. These AI-driven models come in a variety of forms. For instance, AI models that can enhance stock trading is based on a reinforcement learning algorithm (Luo et al., 2019), AI models using fuzzy logic to forecast trends in the values of financial assets and a model based on natural language processing (NLP) that incorporates investor sentiment to forecast stock trading profits (Cohen, 2022).

In the finance industry, forecasting models are some of the most commonly used AI models, using a variety of traditional and non-traditional data sets, in contrast to conventional methods. To estimate consumer loan default, for instance, Óskarsdóttir et al. (2018) combined sociodemographic data with smartphone-based data. In essence, AI-driven forecasting models leverage diverse datasets to generate more nuanced insights quickly, thereby substantially reducing the time and cost required for forecasting. Several AI models have been developed for forecasting transactions in financial markets. To anticipate asset returns, Li and Mei (2020) used a deep learning neural network with two hidden layers. An AI model was created by Sigrist and Hirnschall (2019) to forecast Swiss SMEs' default rates. Based on investor sentiment, Ruan et al. (2020) used machine learning (ML) algorithms to predict stock market returns. To forecast high-frequency asset pricing, Petrelli and Cesarini (2021) integrated several artificial intelligence algorithms. By employing AI to forecast insurance claims, an insurance client can ask for an explanation of why their claim was denied (Rawat et al., 2021).

Financial firms may attain compliance more quickly, in real time, and with fewer resources by using AI-based models (Fabri et al., 2022). Additionally, by spotting previously hidden patterns, AI can improve the efficiency of financial regulatory reporting (Kerkez, 2020). According to Milana and Ashta (2021), ML-driven models are trained on extensive historical data and can consequently, detect concealed fraud patterns by incorporating non-traditional financial data sources. Wyrobek (2020) noted that an organization's risk of financial irregularities can be identified by analysing annual financial statements, which AI-based algorithms can use to uncover fraud tendencies. As per Ahmed et al. (2022), detecting money laundering activity is another effective use for ML algorithms.

Researchers have claimed that financial institutions adopting AI may experience lower operational costs. Kerkez (2020) argued that AI has the potential to lower costs by automating processes like compliance. Moreover, because financial institutions and FinTech lenders can better target their customers thanks to AI's strong credit score evaluation, loan default rates can be decreased (Königstorfer & Thalmann, 2020). Employing AI chatbots also reduce costs of hiring more labour for various customer service tasks (Patil and Kulkarni, 2019). According to Deloitte (2020), businesses can purposefully develop intelligent automation systems by adopting a comprehensive perspective of end-to-end operations to save expenses and increase revenue possibilities.

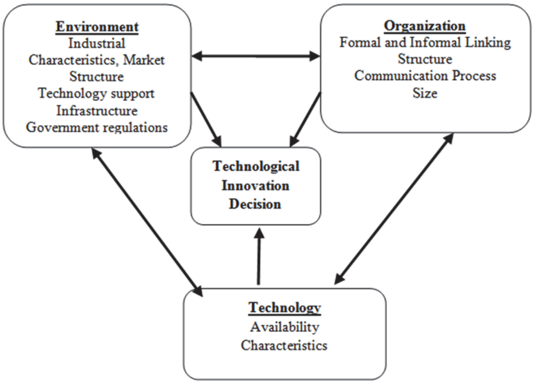
Promoting financial inclusion is an important aspect of financial services companies' operations that aligns with achieving SDGs (Peric, 2015). AI adoption resolves one of the major barriers to financial inclusion, information asymmetry, by generating extensive personal data through AI access to diverse social networks and online shopping platforms(Yang & Zhang, 2020). With AI-powered mobile devices, individuals could potentially access credit, save and deposit funds, make payments and conduct all manners of financial transactions on the go. This promotes financial inclusion by enabling limited-income people to access services typically unavailable through traditional banking channels (Van Hove & Dubus, 2019).

However, the integration of AI into financial service operations has faced challenges. Despite significant investments in groundbreaking technological initiatives within the financial sector, many financial institutions find it challenging to scale and widely integrate AI despite these efforts. Chui and Malhotra (2018) assert that the predominant barrier thwarting banks' endeavours is the absence of a clearly defined AI strategy. Other challenges identified include deficient data infrastructure (Milana & Ashta, 2021), inadequate legacy infrastructure (Kalyanakrishnan et al., 2018) and outdated personnel strategy (Kruse et al., 2019) and wrong operational approach (Lee & Shin, 2020).

3. Methodology

The research commenced with identifying its aim to examine the drivers behind AI adoption in South Africa's financial system. Afterwards, an in-depth analysis of the existing literature was undertaken, leading to the identification of AI adoption drivers using the Technology-Organisation-Environment (TOE) framework. The TOE framework, introduced by Tornatzky et al. (1990), provides a comprehensive overview of the entire innovation process, covering everything from the inception of new ideas to their adoption and integration within a business entity. The TOE framework is built upon the Contingency Theory of Organization, and it chronicles the complete trajectory an organisation experiences when embracing innovation, including its conception, execution, and application. Hence, the TOE framework serves as an extensive model focused on aiding organisations in pinpointing the critical factors that impact the adoption and integration of technological innovation.

The choice of the TOE framework over other innovation theories like diffusion of innovation, dynamics of innovation and disruptive innovation theories and others, was based on its relative adaptability, flexibility and its evolution into a framework that accommodates a wide range of factors (Zhu & Kraemer, 2005). It has been described as a generic theory which has been seen as compatible with and subsuming other theories of innovation adoption, rather than providing a rival explanation (Iacovou et al., 1995; Kuan & Chau, 2001; Lee & Shim, 2007; Rogers, 1995; Zhu et al., 2006). Teo et al. (2003) proposed that the core principle of the TOE framework revolves around organisations adopting technologies that are in sync with the factors from within, outside and surroundings, in line with the organisation's specific contextual attributes. The determinants of innovation adoption are dynamic, as they may differ between organisations or change within the same organisation during the change between different innovations (Zhu et al., 2006). The TOE framework is an organization-level focused theory that delineates three distinct components guiding organisations' innovation adoption decisions (Oliveira & Martins, 2011). As depicted in Figure 2, the three components comprise technological, organisational and environmental factors, and as posited by Tornatzky et al. (1990), each of these factors significantly influences the choice to adopt technological innovation. After an in-depth examination of the literature, Table 1 outlines the factors and diverse perspectives explored as motivators for AI adoption within South Africa's financial services landscape.



The subsequent phase of the research process entailed gathering data via a questionnaire. The sample unit comprised financial services professionals in South Africa. Initially, the participants of the study were contacted through their personal email addresses, sourced from various outlets, including LinkedIn platform for professional networking, corporate portals, and through connections with staff of financial companies who facilitated introductions to their colleagues. To streamline the process and ensure maximum accessibility for participants, the questionnaire was distributed to them through the Microsoft Forms platform. Of the 180 questionnaires dispatched to financial services professionals in the South African financial services industry, 86 were returned, indicating a response rate of 48%. The questionnaire was organised into two primary sections, summarised as follows:

- AI perception and receptiveness: The first section prompted respondents to address various questions to gauge financial services professionals' perception and receptiveness towards AI in South Africa.
- AI adoption drivers: The TOE framework's three contexts were then used to ask participants to rank the perceived relevance of each element influencing AI adoption in South Africa's financial services sector. A 5-point Likert scale was used to measure this, with 1 representing “not at all important” and 5 representing “extremely important.”

The analysis of the collected data was done in two stages. Initially, a descriptive analysis was conducted using statistical tests like mean and variance. The responses to questions in the initial section of the survey were first analysed to gain insights into the present level of AI adoption within South Africa's financial services sector. Moreover, it was designed to demonstrate the respondents' awareness and acquaintance with the application of AI in the country’s financial sector. The responses provided by the participants to the questionnaire’s second part were assessed with mean statistic. The objective was to improve the comprehension of the relative importance of each TOE factor in determining AI adoption.

Table 1. Factors driving AI adoption

	Factors	Literature
Technological factors		
1.	Accessibility to IT infrastructure	Gangwar et al. (2015); Kalyanakrishnan et al., 2018.
2.	Accessibility to quality data	Milana & Ashta, 2021
3.	Ease of integrating AI into financial services	Alsheibani et al. (2018)
4.	Embedded data governance practices	Spanaki et al. (2022); Ransbotham et al. (2017)
5.	Flexibility and scalability of AI technologies	Lee & Shin, 2020
Organisational factors		
6.	Organisational readiness	Richey et al. (2007)

	Factors	Literature
7.	Management leadership and support	Kruse et al. (2019); Rzepka and Berger (2018); Pillai and Sivathanu (2020)
8.	Pursuit of increased efficiency and productivity	Iacovou et al. (1995)
9.	Organisational compatibility	Iacovou et al. (1995)
10.	Employee reluctance to embrace changes resulting from the adoption of AI	Dora et al. (2022); Merhi (2021)
Environmental factors		
11.	Regulatory framework and enforcement	Baker, 2012; Awa et al. (2017); Boyd & Wilson (2017)
12.	Government initiatives and campaigns aimed at encouraging the AI adoption of AI.	Awa et al. (2017)
13.	The competitive environment and customers' expectations	Low et al., 2011; Pillai and Sivathanu (2020)
14.	Cost of implementing AI	Hung et al. (2016)
15.	Access to and support from technology specialists	Aboelmaged (2014)

Source: Author

In the next phase of the research process, a binary logistic regression was conducted to determine the drivers of AI adoption within the TOE contexts. Considering the dependent variable's dichotomous nature and the explanatory variables' attributes, a conditional probability model to be estimated by a logit regression was considered suitable. According to Breen et al. (2018), a logit regression estimates the likelihood of a particular event occurring by considering a range of independent variables. Researchers embrace logistic regression because it provides reliable and unbiased estimates (Alzen et al., 2017). The equation of the logit model transforms the log odds of success into a linear component as follows:

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \sum_{k=0}^{k} x_{ik}\beta_k \qquad i = 1,2,\ldots,N \tag{1}$$

The estimation of the logit model begins by stating the probability that Y=1.The probability that Y=0 is denoted as $1-\hat{P}$, and it signifies when TOE factors do not drive AI adoption. On the other hand, Y=1 is denoted as $\hat{P}$, and it signifies when TOE factors drive AI adoption. This will lead to the following equation:

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X \tag{2}$$

To obtain the anticipated probability that Y=1 for all X values, the following computation of the model takes place:

$$\hat{P} = \frac{e^{\beta_0+\beta_1 X}}{1+e^{\beta_0+\beta_1 X}} \tag{3}$$

The model will be articulated as follows, with the variables acting as factors influencing AI adoption:

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \sum_i^n \delta_i + \sum_j^n \delta_j + \epsilon \tag{4}$$

When Z is replaced with X in the preceding equation, it transforms into:

$$Z = \beta_0 + \delta_1 Technological\ factors + \delta_2 Organisational\ factors + \delta_3 Environmental\ factors + \epsilon \tag{5}$$

Where Z is AI adoption, $\delta(\delta_1, \delta_2, \delta_3)$ are parameters to be estimated and ϵ is the error term. The variables estimated in the logit model are described in Table 2.

Table 2. Description of variables

Variable	Measurement	Expected sign
Dependent variable		
AI adoption	Perception of AI adoption – "Adopted" vs "Not adopted" responses	Not applicable
Independent variables		
Technological factors	Mean of technological factors	+
Organisational factors	Mean of organisational factors	+
Environmental factors	Mean of environmental factors	+

4. Results and Discussion

4.1 General perspective and receptiveness towards AI

Table 3 presents the results of the first part of the questionnaire that gauged the respondents' overall perception, outlook and level of understanding towards AI. The results showed that 56% of respondents held positions in the core operational aspects of South Africa's financial services, while executives and managers accounted for 14%. Those in marketing and Technical/IT functions comprised 15% and 9%, respectively. All the respondents confirmed awareness of the concept of AI. Regarding the level of familiarity with AI, a combined 76% of respondents are either moderately familiar or highly familiar with AI, 8% are extremely familiar, 13% are slightly familiar, while 3% are not at all familiar. Moreover, a combined 78% of respondents moderately or quite well understand the implementation of AI in financial services operations. While 12% understand it to a limited extent, 3% do not understand it at all. Concerning AI adoption in South Africa's financial services sector, 87% of respondents affirmed adoption, while 5% indicated that AI is not adopted. The remaining 8% indicated that no knowledge. Risk management topped the reasons stated by the respondents for AI adoption, with 26% of responses. This was followed by cost saving, improved productivity, robust customer service and better decision making with 21%, 19%, 18% and 14% of responses, respectively. Regarding how receptive the financial services customers are to AI, in relation to its adoption level, many respondents (74%) perceive that AI within South Africa's financial sector is characterized by high adoption. These respondents were divided on the level of receptiveness to AI, with 30 indicating low reception and 34 indicating high reception.

Table 3. Perceptions and receptiveness to AI

	Frequency	Percentage
Function within the financial industry		
Leadership/Managerial	14	16
ICT	9	11
Operations	48	56
Marketing	15	17
Are you familiar with AI technology?		
Yes	86	100
No	0	0
Familiarity level regarding AI		
Completely unfamiliar	3	3
Slightly familiar	11	13
Somewhat familiar	29	34
Very familiar	36	42

	Frequency	Percentage
Exceptionally familiar	7	8
Degree of knowledge regarding AI application in financial service		
No knowledge at all	3	3
Somewhat knowledgeable	10	12
moderately knowledgeable	30	35
Very knowledgeable	37	43
Exceptionally knowledgeable	6	7
Perception of AI adoption in South Africa's financial sector		
Not adopted	4	5
Adopted	75	87
Do not know	7	8
Understanding of the primary motive for AI adoption		
Cost reduction	42	21
Risk mitigation	53	26
High-quality customer service	35	18
Well-informed decision making	27	14
Enhanced productivity	39	19
Others	4	2
Understanding of AI receptiveness and adoption		
High reception, low adoption	10	12
Low reception, high adoption	30	35
High reception, high adoption	34	39
Low reception, low adoption	12	14

4.2 Drivers of AI adoption

4.2.1 Descriptive Analysis

The second part of the questionnaire assessed the respondents' perception of the drivers of AI adoption based on a Likert scale of 1 to 5. As reported in Table 4, three drivers obtained mean ratings of 4 (suggesting very important), while no driver obtained a mean score below 3 (slightly important). This implies that most respondents deem these drivers as holding a certain degree of importance. The ensuing discussion centres on the primary facilitators in each TOE category.

Among the technological factors, "Technological infrastructure accessibility" (A1) emerged as the leading factor propelling AI adoption in South Africa's financial services sector, with a mean rating of 4.14. Aboelmaged (2014) defined the infrastructure described as the fundamental tools and resources needed to apply AI. Gangwar et al. (2015) argued that the implementation of AI requires and requires a strong technology infrastructure. Organisations cannot deploy AI without this prerequisite, which can present a significant barrier (Merhi, 2021). This result suggests that the decision to adopt AI becomes significantly easier with a well-established technological infrastructure in place. The second-ranked technological factor is "Flexibility and scalability of AI technologies" (A5) with a mean score of 3.99. Flexibility refers to a system's ability to adapt to changing requirements, while scalability relates to its capacity to handle an increasing workload. These factors are crucial to AI adoption decisions because as customers' requirements evolve, it is essential to ensure that the AI technology solution in place can adequately meet the rising requirements. These requirements often arise from the need to cope with huge volume of data subsequent to a growing workload, and no matter how much data is generated, it remains futile unless it is organised, comprehended, and meaningful (Sharma et al., 2021). Hence, flexible and scalable AI tools are indispensable. Ben-Daya et al. (2019) argued that technological challenges such as scalability, identification and addressing, data heterogeneity, and computational efficiency, compounded by existing technological constraints, present significant concerns.

Among the organisational factors, the topmost factor driving the adoption of AI in South

Africa's financial services sector is "Support and leadership from senior management" (B3), ranking highest with an average score of 4.01. According to Hsu et al. (2019), senior management's backing is vital when acquiring new technologies, as they often serve as the primary decision-makers within the organization. Moreover, Pillai and Sivathanu (2020) argued that creating a supportive environment by the top management is a critical factor in shaping the adoption of AI technology. indeed, by fostering a supportive environment and providing strategic guidance, business leaders can catalyse organisational readiness for AI adoption and position the organisation for long-term success in the digital age. Organisational readiness (B4) came second with a mean score of 3.82. This factor has been disaggregated into financial readiness and technological readiness (Iacovou et al., 1995; Richey et al., 2007). Organisations must upgrade their technological infrastructure and capabilities to support AI applications effectively. This may involve implementing new software platforms, upgrading hardware systems, and enhancing data management practices to ensure compatibility, scalability, and performance. Additionally, organisations must assess their financial preparedness and develop comprehensive budgeting and funding strategies to support AI adoption initiatives. This may include securing funding from internal sources, seeking external financing options, or exploring partnerships and collaborations to share costs and resources.

Among the environmental factors, “The competitive environment and customers’ expectations” (C5) emerged as the leading factor driving AI adoption with a mean score of 4.25, and in fact, the overall topmost factor across the entire TOE context, indicating its importance. The evolving requirements of customers have continuously prompted financial services companies to enhance their operations through the adoption of AI-driven digitisation. Goodell et al. (2021) stated that this enables them to fundamentally transform their operational approaches, innovate in product and service development, and revolutionise the customer experience. Another important factor in the environmental context is “Regulatory framework and enforcement” (C4), which was ranked second with a mean score of 4.01.

When financial services organisations have a clear understanding of AI regulations in the industry, they tend to feel more confident in adopting AI technologies into their processes. Boyd and Wilson (2017) argued that organizations should stay informed and stay current with new regulations regarding constraints on AI research, development, and utilization. This will lead to a greater sense of confidence and encouragement in the decision to adopt AI.

Table 4. Drivers of AI adoption

No	Drivers of AI adoption	Mean	Variance	Rank
TECHNOLOGICAL FACTORS				
A1	Technological infrastructure accessibility	4.135	0.794	**1**
A2	Availability of structured and quality data	3.691	0.948	3
A3	Ease of integrating AI into financial services	3.413	1.028	4
A4	Embedded data governance practices	3.038	1.151	5
A5	Flexibility and scalability of AI technologies	3.993	0.813	2
ORGANIZATIONAL FACTORS				
B1	Organisational readiness	3.820	0.892	2
B2	Workforce resistance to changes due to AI adoption	3.302	1.190	4
B3	Support and leadership from senior management	4.012	0.823	**1**
B4	Organizational compatibility	3.110	1.197	5
B6	Pursuit of increased efficiency and productivity	3.497	0.915	3
ENVIRONMENTAL FACTORS				
C1	Support from AI technology vendors	3.121	1.242	5
C2	Government programs that motivate AI adoption	3.741	1.058	3
C3	Cost of implementing AI	3.360	1.184	4
C4	Regulatory framework and enforcement	4.010	0.814	2
C5	The competitive environment and customers’ expectations	4.246	0.694	**1**

Source: Author

4.2.2 Binary logistic regression

Table 5 presents the results of the binary logistic regression to assess the likelihood of AI adoption in the financial services sector of South Africa. The results of the Cox & Snell and the Nagelkerke R-Squares showed that the model explained between 0.614 and 0.712 of the variations in the dependent variable, while the Hosmer & Lemeshow p-value of 0.517 affirms model fitness. Overall, the estimates of the logit model revealed that technological factors, organizational factors and environmental factors are all significant factors driving the adoption of AI in South Africa's financial services sector.

The coefficient of technological factors is positive and statistically significant at the 1% level with an odds ratio of 1.049. This suggests that an improvement in technological factors tends to enhance the decision to adopt AI in financial services operations. The corresponding odds ratio indicates that the probability of financial services companies adopting AI increases by 1.049 when the mean of technological factors increases by 1 unit. This finding underscores the importance of technological factors like access to technological infrastructure, quality and structured data, AI flexibility and scalability, ease of integration and data governance in fostering the decision to adopt AI. This finding is consistent with previous studies which argued that the stated technological factors are crucial in determining the decision to adopt AI (Aboelmage, 2014; Ahmad et al., 2021; Alsheibani et al., 2018; Ben-Daya et al., 2019; Gangwar et al., 2015; Merhi, 2021; Sharma et al., 2021). Particularly, this research outcome aligns with the TOE framework, as it agrees with the finding by Gangwar et al. (2015), who used a technological- and organisational variables-driven framework and found that AI adoption is contingent on accessibility to a robust IT infrastructure that is firmly established.

Organisational factors also have a positive and significant result, with an odd ratio of 1.342. Specifically, an improvement in the organizational factors is associated with a rise in the likelihood of the decision to adopt AI. Moreover, the results imply that probability of AI adoption increases by 1.342 when the mean of organizational factors rises by 1 unit. This finding aligns with earlier research that identified organizational factors, such as organisational leadership support (Hsu et al., 2019; Pillai & Sivathanu, 2020), pursuit of increased productivity and efficiency (Pillai et al., 2022) and articulation of clear vision (Merhi, 2021), as key drivers of AI adoption. This research outcome reinforces the argument in extant research that that there is need for a strong and clear connection between the organisation's vision and strategy to drive AI adoption (Duan et al., 2019; Merhi, 2021). The result also supported previous studies' finding that organisational readiness is a crucial driver for AI integration (Richey et al., 2007).

Environmental factors have a positive and significant result with an odd ratio of 1.265. This result affirms that enhanced organizational factors tend to increase the likelihood of deciding to adopt AI. The odds ratio result suggests that an increase in the mean of environmental factors by 1 unit increases the probability of AI adoption by 1.265. This result corroborates previous findings that important drivers of AI adoption include evolving customer requirements (Goodellet al., 2021), regulation and enforcement (Boyd & Wilson, 2017), cost of implementation (Davenport & Ronanki, 2018). Moreover, this result aligns with existing literature (Aboelmaged, 2014; Pillai et al., 2022) that the support offered by technology vendors significantly impacts AI adoption, especially in instances where the organisation lacks technological proficiency. It is also consistent with the argument that financial services companies under pressure from external sources, like competitors and consumers are more likely to implement AI to make decisions and render financial services more quickly (Queiroz et al., 2022).

Table 5. Binary logistic regression results

Variable	B	S.E.	*Sig*	Exp(B)
Technological factors	0.417***	0.139	0.002	1.049
Organisational factors	0.685*	0.326	0.017	1.342
Environmental factors	0.941***	0.376	0.005	1.265

Note: *** and ** indicate 1% and 5% levels of significance, respectively. Cox & Snell; R-Square 0.614; Nagelkerke R-Square 0.712; Hosmer-Lemeshow 6.152, sig. 0.517

5. Conclusion

This paper examined the factors driving AI adoption in South Africa's financial services landscape. The study identified crucial factors influencing AI adoption across technological, organisational, and environmental contexts by employing the TOE framework and conducting a comprehensive analysis of existing literature. Through the methodology of questionnaire-based data collection, statistical analysis, and binary logistic regression, the research investigated the significance of these factors in shaping the decision-making process of financial services companies regarding AI adoption. The findings revealed that South Africa's financial sector is characterised by a high awareness and familiarity with AI, with most respondents acknowledging its adoption and recognising its potential benefits. Key drivers of AI adoption include robust technological infrastructure accessibility, support and leadership from senior management, and the competitive environment coupled with customers' evolving expectations. These factors are pivotal in fostering an environment conducive to AI integration within financial institutions.

Furthermore, the binary logistic regression analysis provided empirical evidence supporting the importance of technological, organisational, and environmental factors in driving AI adoption. The positive and statistically significant coefficients underscored the impact of these factors on the likelihood of AI adoption, highlighting their role in shaping strategic decisions within the financial services sector. Overall, the study contributes to the existing literature by offering insights into the practical aspects of AI adoption dynamics in South Africa, a region experiencing rapid digitisation and technological advancement. The research provides valuable guidance for policymakers, industry stakeholders, and financial institutions seeking to deepen financial inclusion and enhance competitiveness through AI integration by identifying and analysing the operational drivers of AI adoption.

By implication, continued research and monitoring of AI adoption trends in South Africa's financial services sector will be essential for ensuring the effective utilisation of AI technologies and maximising their potential benefits. Additionally, efforts to address existing challenges related to inequality, regulatory frameworks, and technological readiness will be crucial for fostering an inclusive and sustainable AI-driven financial ecosystem in South Africa. Particularly, the following recommendations follow the findings of this study:

First, companies in the financial sector should encourage a culture that welcomes innovation and the integration of AI technology. This might entail educating the public, offering training courses, and offering financial incentives for experimenting with AI solutions. This research specifically recommends that business executives use a top-down strategy to seek out, support, and aggressively promote grassroots innovative projects. According to Bodea et al. (2020) and Hsu et al. (2019), the organisation's executive echelons are the correct authority to determine whether to use AI technology. Thus, it is imperative that leaders of businesses take urgent action to increase awareness and provide guidance regarding AI. It is imperative to reassure the labour force that integrating AI would not jeopardise job security but rather enhance productivity and efficiency. This is particularly crucial given that a considerable proportion of the workforce is shifting from manual labour-focused professions to ones focused on management and supervision. Executives in the firm should also set aside funds for employees to upgrade their skills and cultivate a growth mindset-fostering learning culture. According to Nieto-Rodriguez and Vargas (2023), managers must prepare their staff to shift to AI. Firms can access, explore, and refine a wider range of concepts from their talent pool if senior management is intentional and provides strong financial support.

Furthermore, policymakers should endeavour to create comprehensive and unambiguous legislative frameworks that control AI use in financial services. These regulations should address data privacy, algorithm transparency, and ethical AI practices. Working with international standards organisations and industry players can aid in developing guidelines that strike a balance between innovation, risk management, and consumer protection. To safeguard the reputation of organisations looking to improve their operational frameworks and procedures in the market, proactive legislation establishing more transparent and unambiguous AI rules and guidelines suited for financial services procedures is necessary. Organisations should also devote resources to internal governance mechanisms, training programmes, and compliance operations to enhance adherence to ethical norms and regulatory obligations. Moreover, to cultivate trust and confidence among finance sector practitioners, customers, and other stakeholders, it is imperative to prioritise openness, accountability, and ethical AI practices. Organisations can use AI technology to increase operational efficiency, improve decision-making, and gain a competitive edge while reducing possible risks and liabilities associated with AI adoption by embracing legal frameworks and ethical principles.

Moving forward, research has a lot to contribute to advancing knowledge on AI adoption in the South African financial services sector and providing practical guidance for financial institutions and policymakers. Future research could explore cross-sectoral studies to compare AI adoption drivers across different industries to enhance understanding of commonalities and differences in adoption patterns. Comparative studies on the impact of regulatory frameworks on AI adoption across different sectors could also be conducted to inform policymakers and financial institutions in navigating regulatory challenges effectively. Moreover, future research could focus on identifying effective strategies for overcoming barriers to AI adoption and facilitating successful implementation in the financial services sector. This could involve case studies or experimental research aimed at evaluating the effectiveness of different implementation approaches in diverse organizational contexts.

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