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AI-Driven Business Model Innovation: The Impact of AI Integration Platform as a Service (AIPaaS) in the Financial Service Industry in Johannesburg, South Africa

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AI-Driven Business Model Innovation: The Impact of AI Integration Platform as a Service (AIPaaS) in the Financial Service Industry in Johannesburg, South Africa



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Submitted in Partial Fulfilment of the Requirements for the Degree of Master of Management in Entrepreneurship and New Venture Creation.

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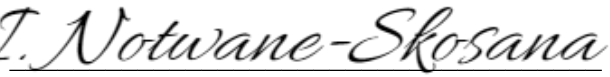
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Abstract

This study explores the adoption of Artificial Intelligence Platform as a Service (AIPaaS) in Johannesburg's financial services industry, with a focus on its impact on business model innovation (BMI) and organisational efficiency. Although Johannesburg is South Africa's financial hub, adoption remains inconsistent due to regulatory uncertainty, legacy systems, and institutional resistance.

Framed within Technopreneurship theory and supported by the Unified Theory of Acceptance and Use of Technology (UTAUT), Corporate Entrepreneurship, and Business Model Innovation frameworks, the research offers an integrated lens on emerging technology adoption in complex organisational environments.

A quantitative methodology was applied using structured surveys via Qualtrics, targeting compliance officers, decision-makers, and data professionals. While initial factor analysis suggested strong convergence, constructs were analysed independently to preserve theoretical integrity and allow for more precise interpretation—particularly relevant given the novelty of the topic.

Findings highlight perceptions of AIPaaS and innovation dynamics as key predictors of both BMI and organisational performance. Barriers such as regulatory complexity, data governance concerns, and outdated infrastructure emerged as both constraints and catalysts for technopreneurial opportunity.

The study concludes with targeted recommendations aimed at strengthening innovation-enabling environments, addressing systemic barriers, and supporting cross-sector collaboration to enhance AIPaaS uptake in Johannesburg's financial ecosystem.

Keywords: *AIPaaS, Technopreneurship, Business Model Innovation, Organisational Efficiency, Emerging Markets, Financial Services, UTAUT, Corporate Entrepreneurship, AI Adoption*

Chapter 1: Introduction

1.1 Background and Context

Global Context of AI in Business

Artificial Intelligence (AI) has emerged as a transformative force, reshaping industries by enabling innovative solutions, optimising resource allocation, and supporting data-driven strategies (Lee et al., 2019). Initially viewed as a futuristic tool for niche applications, AI has become indispensable in fields such as healthcare, retail, and manufacturing, driving both incremental efficiencies and groundbreaking innovations (Lee et al., 2019). A significant number of organisations across industries have embraced AI to maintain competitiveness, develop customer-centric strategies, and streamline operational workflows (Anica-Popa et al., 2021). AI's capacity to adapt and evolve makes it a versatile tool that permeates nearly every facet of business operations, fostering both incremental improvements and disruptive innovation.

Among the most notable advancements in AI technology is *Artificial Intelligence Platform as a Service (AIPaaS)*, a cloud-based solution that enables organisations to leverage pre-configured AI capabilities, such as machine learning and predictive analytics. AIPaaS democratises AI by reducing the need for extensive technical expertise, allowing businesses to deploy AI solutions with speed and cost efficiency (Deloitte, no date; J.P. Morgan Chase, 2023). Major technology firms such as Amazon, and Microsoft have pioneered AIPaaS offerings, with Standard Bank of South Africa edging behind, which facilitate fraud detection, improve compliance monitoring, and enable hyper-personalised customer experiences within the financial industry (Amazon Web Services, 2024; Microsoft, 2023; Standard Bank South Africa, 2024).

Globally, financial institutions have leveraged AIPaaS to transform operations. JP Morgan's dynamic risk assessment and Mastercard's fraud detection capabilities exemplify its strategic value in modernising back-end and customer-facing processes (Ernst & Young, 2024b; J.P. Morgan Chase, 2023). Despite widespread adoption in advanced markets, emerging economies like South Africa have been slower to implement these technologies, creating untapped potential for innovation and efficiency gains.

Johannesburg's Financial Industry

Johannesburg is home to South Africa's most advanced financial ecosystem that contributes significantly to the national economy (South African Government, 2023; University of Johannesburg Business School, 2022). The city's financial industry comprises of banks, insurance firms, wealth management companies, and fintech startups, reflecting a well-developed and diverse ecosystem. Johannesburg's financial institutions boast advanced technological infrastructure, often drawing comparisons to global financial centres such as London and New York. Despite this sophistication, the industry faces challenges that hinder its ability to leverage emerging technologies like AIPaaS fully.

Key challenges include economic instability, fraud prevalence, and a pressing need for financial inclusion. According to Manamela (2023), while Johannesburg's financial industry demonstrates resilience and adaptability, it often lags in adopting cutting-edge technologies due to institutional hesitance and stringent regulatory requirements. This gap creates a compelling need to explore innovative solutions, such as AIPaaS, that can address these challenges while maintaining competitiveness.

AIPaaS offers a strategic solution to these challenges by enhancing operational efficiency and enabling *business model innovation (BMI).* For example, banks can use AIPaaS to introduce dynamic lending models tailored to underserved communities, while insurance firms can leverage AI platforms to develop personalised policies based on behavioural data (Ernst & Young, 2024c; Foss & Saebi, 2018).

Despite its potential, the adoption of AIPaaS in Johannesburg remains limited. Institutional hesitance, driven by concerns about integration complexity, resource requirements, and cultural resistance, has slowed the pace of implementation. Additionally, regulatory constraints, particularly under the Protection of Personal Information Act (POPIA), create apprehension among organisations wary of compliance risks. POPIA imposes stringent requirements for data protection and encryption, which, while necessary, can complicate the integration of AI systems. This dynamic highlight a critical gap in understanding how AIPaaS can be leveraged to meet these regulatory demands while driving innovation and efficiency.

Significance of AIPaaS

AIPaaS holds the potential to drive business model innovation (BMI) and enhance efficiency within Johannesburg's financial industry. It redefines how financial institutions create, deliver, and capture value, enabling innovations such as flexible loan products and behavioural data-driven insurance policies (Foss & Saebi, 2018). These capabilities not only improve customer satisfaction but also strengthen financial resilience by reducing default risks and enhancing loyalty (Venkatesh et al., 2016).

Operationally, AIPaaS automates repetitive tasks, enhances resource allocation, and mitigates errors, making it a critical tool for compliance with regulations like POPIA (Deloitte, 2022; Ernst & Young, 2024a). The technology's dual role in innovation and efficiency highlights its strategic importance, offering Johannesburg's financial institutions a path to remain competitive in a rapidly evolving global market.

1.2 Problem Statement

Core Issues

Despite Johannesburg's financial industry being technologically advanced and globally competitive, the adoption of Artificial Intelligence Platform as a Service (AIPaaS) remains notably limited. This reluctance stems from three interconnected challenges:

1. **Organisational Resistance**: A number of institutions exhibit hesitance toward emerging technologies due to cultural inertia, fear of disruption, and an insufficient readiness to integrate AI capabilities into legacy systems. These barriers hinder proactive innovation and delay the adoption of transformative tools (Urban, 2017; Urban & Maphumulo, 2022).
2. **Data Security Concerns**: The implementation of AIPaaS necessitates handling vast amounts of sensitive customer data, raising concerns about privacy breaches and compliance risks. South Africa's Protection of Personal Information Act (POPIA) imposes stringent data security requirements, intensifying institutional apprehensions (Kgoale & Odeku, 2023).
3. **Regulatory Stringency**: The stringent compliance environment in South Africa's financial industry, while necessary for maintaining stability and trust, often discourages adoption of technologies perceived as adding complexity. This results in a cautious approach to AIPaaS, limiting innovation (Kgoale & Odeku, 2023).

Impact of the Problem

The limited adoption of AIPaaS has significant implications for Johannesburg's financial industry. Institutions failing to integrate this transformative technology risk losing opportunities to innovate business models, enhance customer experiences, and optimise operations. Moreover, this hesitance leaves Johannesburg's financial institutions at a disadvantage compared to global peers that have embraced AI-driven platforms to redefine their competitive edge (Deloitte, 2022). Addressing these barriers is essential to maintaining the city's leadership in financial innovation and regional influence.

1.3 Research Objectives

This study is guided by two primary objectives:

a. **Investigate the Role of AIPaaS in Fostering Innovation in Business Models Within Johannesburg's Financial Industry**
    - This objective aims to understand how AIPaaS supports the reconfiguration of business models to enhance value creation and delivery.
    - It explores the technology's potential to facilitate the development of innovative products and services, addressing the evolving demands of customers and the dynamic market environment.

b. **Examine the Impact of AIPaaS on Organisational Efficiency in Johannesburg's Financial Industry**
    - This objective evaluates the capacity of AIPaaS to optimise operational processes, improve resource allocation, and streamline compliance efforts.
    - It seeks to identify how AIPaaS mitigates operational challenges specific to Johannesburg's financial landscape, thereby enhancing overall organisational effectiveness.

1.4 Research Hypotheses

The study evaluates the following hypotheses, developed in alignment with its objectives:

H1: AIPaaS adoption positively influences business model innovation in Johannesburg's financial services industry.

- This hypothesis explores the premise that AIPaaS drives transformative changes in business models. It examines the technology's role in enabling institutions to innovate

offerings, enhance customer engagement, and optimise value creation, delivery, and capture mechanisms.

H2: AIPaaS adoption has a positive effect on organisational efficiency within Johannesburg's financial industry.

- This hypothesis posits that integrating AIPaaS leads to significant operational efficiency improvements. Key areas of focus include automation of routine processes, reduction of human error, and streamlined compliance with regulatory frameworks.

Through these hypotheses, the study aims to contribute insights into the strategic potential of AIPaaS to advance innovation and efficiency within an emerging market context. The findings will address existing research gaps, offering empirical insights into how AI adoption reshapes financial services in Johannesburg.

1.5 Research Questions

This study is guided by two key research questions designed to explore the adoption and transformative potential of Artificial Intelligence Platform as a Service (AIPaaS) within Johannesburg's financial industry. These questions frame the investigation into how AIPaaS drives organisational efficiency and supports business model innovation.

a. **What is the impact of AIPaaS on organisational efficiency in Johannesburg's financial industry?**
    - This question evaluates the ability of AIPaaS to streamline processes, reduce operational costs, and enhance productivity. Given the competitive nature of Johannesburg's financial ecosystem, operational efficiency is pivotal for maintaining profitability and compliance. The study examines how AIPaaS addresses inefficiencies in legacy systems to improve overall organisational effectiveness.

b. **What is the statistical relationship between AIPaaS adoption and business model innovation?**
    - This question explores the role of AIPaaS in enabling business model innovation (BMI) by transforming value creation, delivery, and capture mechanisms. It investigates the technology's impact on facilitating the

development of innovative products, such as personalised financial solutions, and supports data-driven strategies that enhance competitive positioning within a dynamic market.

1.6 Rationale and Significance of the Study

The rationale for this study is rooted in the limited academic exploration of Artificial Intelligence Platform as a Service (AIPaaS) adoption in emerging markets, particularly within Africa's financial industry. Johannesburg, as South Africa's financial nucleus, offers a strategic context for examining how AIPaaS might address pressing industry challenges such as data security, complex regulatory compliance, and organisational resistance to technological change. This study responds to several identified gaps: the absence of research on AIPaaS within highly regulated industries; the limited understanding of how different professional roles within organisations perceive AIPaaS; and the need to situate global AI trends within Johannesburg's distinctive economic and organisational context.

The study's significance is both academic and practical. Academically, it contributes to the growing body of knowledge on AI adoption and business model innovation (BMI), particularly in under-researched contexts. It offers empirical insights into how AIPaaS influences organisational efficiency and supports BMI, thereby advancing existing theoretical frameworks. Practically, the research provides financial decision-makers in Johannesburg with strategic guidance on integrating AIPaaS into their operations, and it recommends policy interventions to create an enabling environment for AI innovation. Ultimately, this study seeks to bridge the gap between theory and practice by positioning AIPaaS as a strategic lever for innovation and operational transformation in Johannesburg's financial industry.

1.7 Definitions of Critical Terms

Establishing precise definitions ensures a consistent analytical framework. The following key terms are integral to this study:

- **Artificial Intelligence Platform as a Service (AIPaaS)**: A cloud-based service providing pre-configured AI tools, such as machine learning and predictive analytics, that streamline integration into organisational workflows. This minimises reliance on in-house expertise and accelerates innovation deployment (Mucha & Seppala, 2020).

- **Business Model Innovation (BMI)**: The transformation of value creation, delivery, and capture mechanisms within organisations, aimed at maintaining competitive advantage. Technologies like AIPaaS drive this innovation, enabling businesses to adapt to market changes (Foss & Saebi, 2017).
- **Organisational Efficiency**: The effective utilisation of resources to enhance productivity and reduce costs while sustaining quality standards. Efficiency gains often result from automation and scalability through AIPaaS solutions (Ernst & Young, 2024c).
- **Innovation in Financial Services**: The introduction of advanced financial products, services, or systems to increase competitiveness and meet customer demands. AIPaaS contributes to this by offering predictive analytics and data-driven insights (Urban, 2017).
- **Data Security**: Protocols and technologies that safeguard sensitive information from breaches and misuse. Effective AIPaaS implementation requires adherence to regulations like South Africa's Protection of Personal Information Act (POPIA) (South African Government, 2021).
- **Regulatory Compliance**: Conformance to financial regulations, including POPIA and Basel III, which influence technology adoption by imposing requirements for secure data handling and operational transparency (Javaid et al., 2022; Kgoale & Odeku, 2023; South African Government, 2021).
- **Organisational Resistance to Change**: The reluctance to adopt new technologies due to concerns about disruption, cost, or cultural inertia. Addressing such resistance is vital for successful AIPaaS adoption (Ernst & Young, 2024c; Urban, 2017).

1.8 Methodological Overview

The study followed a structured quantitative methodology to examine the adoption of Artificial Intelligence Platform as a Service (AIPaaS) within Johannesburg's financial industry. A convenience sampling strategy was used, initially targeting professionals across decision-making, compliance, and technical roles, with a snowball effect expanding participation. Data was collected via structured surveys administered through Qualtrics, ensuring consistency and ethical compliance. Statistical analysis was conducted using SPSS for descriptive statistics, reliability checks, and regression analysis, while JASP was used to validate results and support exploratory factor analysis through advanced visual outputs. This approach enabled a robust

examination of organisational perceptions, barriers, and the strategic impact of AIPaaS adoption.

1.9 Scope and Delimitations

1.9.1 Geographic Scope

The study is situated within Johannesburg, South Africa's financial hub, serving as a focal point for examining AIPaaS adoption in the African financial market.

1.9.2 Industrial Scope

The research primarily explores the banking and insurance industries, recognised as integral to Johannesburg's financial ecosystem. While the primary focus remains on these industries, insights from affiliated domains, such as wealth management, are incorporated when relevant to enrich the findings.

1.9.3 Thematic Focus

The study examines three central themes:

- The potential of AIPaaS to enhance organisational efficiency.
- Its capacity to drive business model innovation.
- Barriers to adoption, including regulatory, technical, and organisational challenges.

1.9.4 Delimitations

- Non-financial industries, such as healthcare and retail, are excluded to maintain a concentrated thematic scope.
- The study focuses on current adoption trends rather than historical or longitudinal analyses of AIPaaS implementation.

1.10 Research Gaps and Conceptual Framework

1.10.1 Identifying Gaps

Interest in AIPaaS and its impact on BMI continues to grow, yet significant research gaps remain, especially within emerging markets like Johannesburg. Existing studies predominantly explore AI adoption in developed economies, providing limited insights into the distinct challenges and opportunities faced by South African financial institutions. While extensive research highlights the operational benefits of AIPaaS in global financial hubs, insufficient

attention is given to its potential for addressing local issues such as financial inclusion and infrastructural constraints (Ali et al., 2023; Sjödin et al., 2021).

Another gap involves the absence of role-specific analyses in studies on AIPaaS adoption. Many investigations approach organisations as homogenous entities, overlooking the diverse perspectives of IT professionals, compliance officers, and executives. This generalisation restricts understanding of how varying viewpoints shape adoption strategies and influence the attainment of BMI objectives. Research exploring these nuances could reveal critical insights into the relationship between organisational roles, technology uptake, and innovation outcomes.

Additionally, the scarcity of longitudinal studies poses a significant limitation. Current research primarily relies on cross-sectional data, offering only a snapshot of AIPaaS adoption. Longitudinal approaches could yield deeper insights into how AI integration affects organisational performance, customer satisfaction, and market competitiveness over time.

1.10.2 Conceptual Framework

To address these gaps, the study introduces a conceptual framework linking AIPaaS adoption, organisational dynamics, and BMI outcomes. This framework draws from established theories, including the Unified Theory of Acceptance and Use of Technology (UTAUT) and business model innovation frameworks, while adapting to the unique context of Johannesburg's financial industry.

Key Components of the Framework

1. **AIPaaS Adoption (Independent Variable)**: Factors influencing adoption, including perceived usefulness, technical integration, and regulatory compliance, are explored. AIPaaS is framed as the catalyst for enabling organisational improvements and sparking innovation.
2. **BMI Outcomes (Dependent Variable)**: AIPaaS adoption is connected to measurable innovation results, such as advanced product offerings, enhanced customer engagement, and streamlined operations. This highlights AIPaaS's ability to address economic and regulatory complexities in Johannesburg, ensuring competitiveness and sustainable growth.

3. **Organisational Dynamics**: Leadership, innovation culture, and cross-departmental collaboration are positioned as critical enablers of successful adoption. External factors, such as market competition and evolving customer needs, are incorporated to reflect the pressures driving organisations to embrace transformative technologies.

Justification for the Focus on Johannesburg

Johannesburg's financial industry serves as an ideal context due to its centrality in South Africa's economy and growing influence in regional markets. Financial institutions in Johannesburg operate within a dynamic environment shaped by rapid technological evolution, regulatory demands, and diverse customer preferences. This study aims to provide both theoretical advancements and actionable insights for organisations seeking to leverage AIPaaS to achieve business model innovation and operational efficiency in such a complex setting.

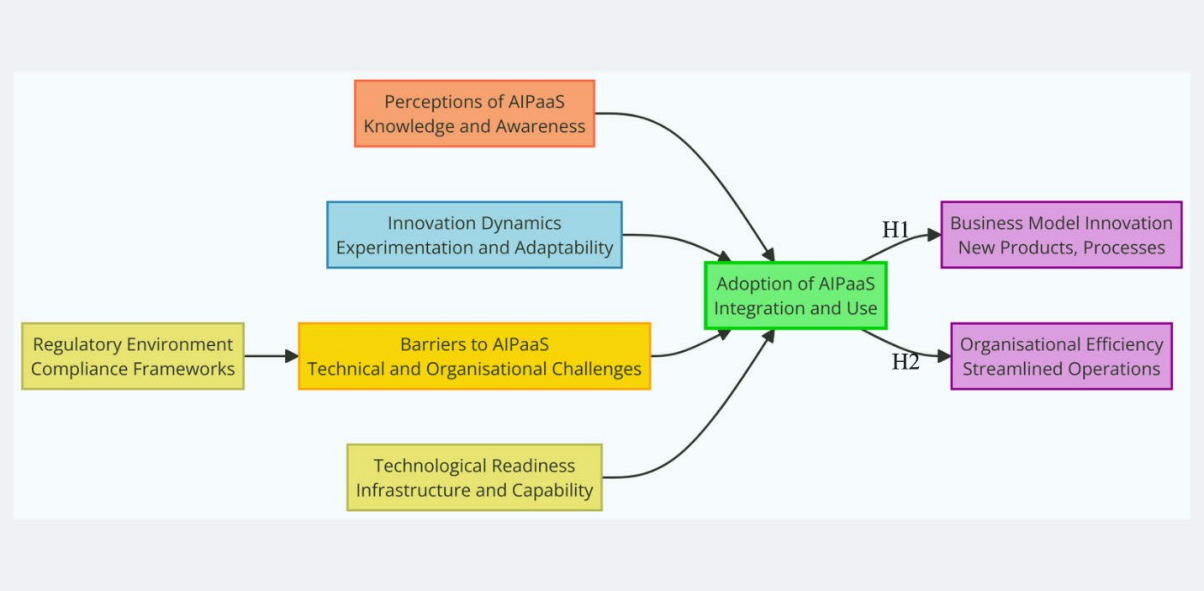


Figure 1 Conceptual Framework for AIPaaS Adoption and Impact on BMI and Organisational Efficiency

1.11 Structure of the Research Report

This report is organised into six chapters, each contributing to the systematic development of the study:

Chapter 1: Introduction – Establishes the context of the research, articulates the objectives, research questions, and outlines the conceptual framework guiding the investigation.

Chapter 2: Literature Review – Reviews scholarly and contextual literature related to AIPaaS, business model innovation (BMI), and organisational efficiency, identifying gaps that the study aims to address.

Chapter 3: Methodology – Details the quantitative research design, sampling strategy, data collection process, and the analytical procedures used to ensure methodological rigour.

Chapter 4: Data Analysis and Results – Provides a comprehensive account of the statistical analyses, supported by tables and figures, and integrates key qualitative insights where applicable.

Chapter 5: Discussion and Recommendations – Reflects on the findings within the context of the theoretical frameworks and existing literature, offering strategic and policy-oriented recommendations.

Chapter 6: Conclusion – Concludes the study by summarising its main contributions, noting its limitations, and suggesting directions for future research.

1.12 Chapter Summary

This chapter introduced the study's investigation into the adoption of Artificial Intelligence Platform as a Service (AIPaaS) within Johannesburg's financial industry, highlighting its potential to drive business model innovation and improve organisational efficiency. The context was framed within both global and local perspectives, acknowledging barriers such as regulatory constraints, economic uncertainty, and internal organisational resistance.

The chapter outlined the research problem, set out the objectives and research questions, and introduced hypotheses linking AIPaaS adoption with innovation and efficiency outcomes. It also addressed research gaps and presented the conceptual framework guiding the analysis. Key concepts were clearly defined to ensure terminological consistency.

The methodological overview presented a quantitative design supported by structured survey data and statistical tools. The scope and delimitations specified a focus on Johannesburg's financial institutions, particularly in the banking and insurance industries.

In sum, this chapter laid the foundation for a structured, contextually grounded inquiry. Chapter 2 now follows with a critical review of relevant literature and theoretical perspectives.

Chapter 2: Literature Review

2.1 Introduction

The literature review serves as a critical foundation for this study, exploring existing research, theories, and frameworks pertinent to the adoption of Artificial Intelligence Platform as a Service (AIPaaS) within Johannesburg's financial industry. Framing the research within broader discussions on technological innovation and business model transformation, this chapter contextualises key constructs underpinning the study: Perception of AIPaaS, Impact on Business Model Innovation (BMI), Innovation Dynamics, Business Model Innovation Barriers, and Future Outlook. These constructs are examined within Johannesburg's technological and industrial landscape as South Africa's economic nucleus.

The objective of this chapter is to establish the theoretical and empirical bases of the study, identify gaps in the existing literature, and justify the research focus. Globally, AIPaaS has been recognised as a transformative tool in financial services, enabling organisations to optimise processes, improve decision-making, and adapt to shifting market demands (Lee & Baucus, 2019). However, Johannesburg's unique position as South Africa's financial hub presents specific opportunities and challenges shaped by its regulatory environment, technological capabilities, and economic context.

This chapter's structure aligns with the study's objectives, progressing from an analysis of theoretical frameworks to an in-depth exploration of the identified constructs. The discussion begins with technological adoption theories, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), extending to frameworks on business model innovation and corporate entrepreneurship. It then critically examines existing research on the core constructs, integrating global and local perspectives.

Johannesburg provides an ideal context for this research, given its critical role in South Africa's financial industry. As the anchor of the country's financial industry, Johannesburg exemplifies both progress and obstacles in the adoption of AI technologies. Although financial institutions in the city are increasingly exploring innovative solutions, barriers such as outdated systems, regulatory complexities, and skills shortages continue to impede widespread adoption (Ernst & Young, 2023). In addressing these issues through a comprehensive review of the literature,

this chapter give emphasis to the study's relevance and timeliness, offering insights that bridge theoretical depth and practical application.

2.2 Theoretical Frameworks

This study draws on an integrated theoretical foundation to examine the adoption of Artificial Intelligence Platform as a Service (AIPaaS) in Johannesburg's financial industry. The frameworks applied include the Unified Theory of Acceptance and Use of Technology (UTAUT), business model innovation (BMI), corporate entrepreneurship, and technopreneurship. Together, they provide a multidimensional lens through which the interaction between technology, innovation, and organisational behaviour can be critically analysed.

The UTAUT model, developed by Venkatesh et al. (2016), offers a foundational understanding of technology acceptance and use. It outlines four primary determinants—performance expectancy, effort expectancy, social influence, and facilitating conditions—that influence behavioural intention to use a technology. UTAUT has been widely applied in studies of technological diffusion across organisational contexts. In this research, it provides a scaffold for evaluating how professionals within Johannesburg's financial institutions perceive and respond to AIPaaS, a relatively novel AI-based technological solution. Importantly, UTAUT allows for an exploration of adoption across roles such as compliance officers, data specialists, and decision-makers, whose expectations and operating conditions differ markedly.

Business model innovation theory, particularly as conceptualised by Foss and Saebi (2017), complements UTAUT by shifting the focus from individual acceptance to organisational transformation. BMI theory interrogates how organisations alter their value creation, delivery, and capture mechanisms in response to environmental or technological change. For financial institutions in Johannesburg, adopting AIPaaS is not merely about operational improvement—it presents an opportunity to redefine customer interactions, introduce new digital products, and streamline compliance and fraud management processes. As such, BMI serves as a critical framework for understanding how AIPaaS can lead to structural innovation beyond incremental process improvements.

Corporate entrepreneurship theory further sharpens this focus by examining internal drivers of innovation such as organisational culture, leadership support, and employee autonomy. Johannesburg's financial institutions operate in a context characterised by regulatory rigidity and risk aversion. Corporate entrepreneurship helps explain the enabling or inhibiting factors that determine whether institutions are capable of integrating disruptive technologies like AIPaaS into their strategic architecture (Urban, 2017).

However, the current study gives particular attention to technopreneurship—a conceptual bridge between technology adoption and entrepreneurial thinking within institutional frameworks. Technopreneurship refers to the process whereby individuals or firms pursue business opportunities by leveraging digital technologies to create or improve value (Giones & Brem, 2017). It combines the innovative drive of entrepreneurship with the capabilities of emerging technologies, offering a compelling lens for understanding AI adoption in fast-evolving industries.

In Johannesburg's financial industry, technopreneurship is especially relevant. Institutions operating under legacy constraints must navigate an evolving regulatory environment while competing with agile fintech entrants (Masenya, 2021). This context demands not just technology implementation, but entrepreneurial orientation—risk-taking, innovation-seeking, and strategic agility. Technopreneurial thinking enables decision-makers to see AIPaaS as more than a compliance or operational tool; it frames it as a strategic enabler of organisational renewal. Furthermore, it supports the case for intrapreneurship, encouraging internal teams to experiment with AI capabilities in product development, service delivery, and customer engagement, despite regulatory uncertainties or resource constraints.

Summatively, the fusion of UTAUT, BMI, corporate entrepreneurship, and technopreneurship provides a robust theoretical foundation for this study. It allows for a nuanced understanding of AIPaaS adoption that acknowledges both structural dynamics and human agency, offering insights into how Johannesburg's financial institutions can navigate and lead within the AI-driven transformation of financial services.

2.3 Perception of AIPaaS

2.3.1 Awareness and Familiarity

Awareness and familiarity are pivotal determinants of AIPaaS adoption. According to the Unified Theory of Acceptance and Use of Technology (UTAUT), constructs such as performance expectancy and social influence directly correlate with an individual's awareness of new technologies (Venkatesh et al., 2016). In advanced financial centres like Singapore and London, widespread familiarity with AIPaaS is facilitated by institutional training programmes, digital transformation policies, and a well-established innovation culture (Karuppiah et al., 2023; Ophoff & Miller, 2019; Pandey & Sergeeva, 2022).

In contrast, Johannesburg's financial institutions exhibit uneven levels of familiarity. Aderibigbe et al. (2023) link this knowledge gap to a fragmented technological infrastructure and overreliance on vendor-led education. Vendor interactions often focus on technical implementation without engaging broader organisational stakeholders, resulting in a shallow understanding of AIPaaS's strategic potential. This role-specific awareness gap is especially stark between IT professionals—who are typically more informed—and compliance or legal teams, who remain peripheral to technological discourse (Vallentyn, 2021).

Technopreneurship theory offers a valuable lens through which to interpret this fragmentation. Giones and Brem (2017) emphasise entrepreneurial alertness and opportunity recognition as core to technopreneurial success. In a context like Johannesburg's, where AI remains emergent, fostering technopreneurial thinking across roles could act as a leveller—bridging gaps in familiarity and promoting a culture of proactive engagement. By enabling cross-functional workshops and shared innovation initiatives, institutions could nurture the kind of interdepartmental fluency necessary for effective AI integration.

2.3.2 Perceived Usefulness and Effectiveness

Perceived usefulness and effectiveness play a crucial role in determining whether a technology like AIPaaS is embraced. In UTAUT, performance and effort expectancy shape this perception. Globally, AIPaaS implementations have demonstrated measurable impacts—reducing manual workloads, enabling predictive analytics, and streamlining compliance efforts (Yaiprasert & Hidayanto, 2024).). In practice, banks such as HSBC and Citibank use AIPaaS for fraud

detection and customer service, reflecting its tangible value in high-stakes environments (Citigroup, 2024; HSBC Group, 2024).

In Johannesburg, the picture is more complex. While decision-makers acknowledge AIPaaS's potential in areas like credit risk analysis and data security, perceptions vary across organisational levels. Compliance officers often perceive AIPaaS as a liability due to its data dependencies and perceived incompatibility with POPIA (Ernst & Young, 2024a). Achmat (2023) found that institutions only endorsed AIPaaS when they observed clear, quantifiable improvements, highlighting the importance of evidence-based adoption narratives.

Technopreneurship and corporate entrepreneurship both stress strategic vision and risk-taking. Urban and Maphumulo (2021) argue that firms with entrepreneurial orientations are more likely to convert uncertainty into innovation. When perceived effectiveness is framed not just in terms of efficiency but strategic agility, AIPaaS's value becomes more widely accepted. These frameworks suggest that the integration of AIPaaS requires a recalibration of expectations, positioning it as a tool for long-term transformation rather than immediate return on investment.

2.3.3 Challenges in Perception

Resistance to AIPaaS adoption is often rooted in organisational culture, regulatory ambiguity, and role-specific misunderstandings. The UTAUT framework identifies "social influence" and "facilitating conditions" as key inhibitors when institutions lack aligned support systems (Venkatesh et al., 2016). This is particularly evident in hierarchical organisations where scepticism at middle management levels can halt innovation (Murimbika & Urban, 2013; Ophoff & Miller, 2019).

Corporate entrepreneurship theory adds further nuance, identifying culture, leadership, and structural support as prerequisites for successful innovation (Urban, 2017). Institutions that nurture innovation champions and support "safe-to-fail" environments are more likely to overcome adoption resistance. Conversely, firms bound by rigid compliance norms or legacy systems tend to delay or avoid AI initiatives altogether (Murimbika & Urban, 2013).

Technopreneurship again emerges as a viable solution. It encourages a mindset where experimentation, agility, and iterative learning are prioritised over strict conformity. Urban and Verachia (2019) note that Johannesburg's financial institutions have begun adopting innovation accelerators and pilot labs to test AI tools like AIPaaS. These initiatives, although nascent, signal a shift toward more entrepreneurial models of technology integration. Masenya (2021) supports this, observing that institutions fostering technopreneurial capabilities are better positioned to internalise emerging technologies and translate them into sustainable competitive advantages.

2.4 Impact on Business Model Innovation (BMI)

2.4.1 The Role of AIPaaS in BMI

Artificial Intelligence Platform as a Service (AIPaaS) is rapidly emerging as a transformative enabler of business model innovation (BMI) within the global financial landscape. As defined by Foss and Saebi (2017), BMI entails redefining the logic by which organisations create, deliver, and capture value. In the context of Johannesburg's financial institutions, where innovation is increasingly linked to digital transformation imperatives, AIPaaS holds the potential to restructure traditional models and respond proactively to market and regulatory pressures (CIO South Africa, 2023; Deloitte, 2022).

Globally, leading institutions like J.P. Morgan and Goldman Sachs have integrated AIPaaS into investment decision-making, fraud detection, and customer analytics, driving enhanced speed and precision in strategic functions (Forbes Finance, 2024; J.P. Morgan Chase, 2023). These firms illustrate how platforms leveraging machine learning, predictive analytics, and automation reshape internal processes and unlock new value propositions. For instance, Goldman Sachs' use of AIPaaS-enabled platforms to automate due diligence in credit decisions demonstrates its BMI impact in real-time environments.

Johannesburg's financial industry, while still maturing in this space, exhibits promising early-stage engagement. Financial institutions are exploring AI-powered micro-loan products and fraud analytics tools to address local challenges, such as financial exclusion and systemic inefficiencies (CIO South Africa, 2023). Although fragmented, these efforts signal a strategic shift towards leveraging AIPaaS as a foundational capability for reimagining service delivery and customer engagement.

However, institutional barriers such as legacy IT infrastructure, limited data integration capabilities, and regulatory constraints—particularly under South Africa's Protection of Personal Information Act (POPIA)—have slowed widespread adoption (Ernst & Young, 2024a). From a UTAUT perspective, this reflects limited facilitating conditions, despite strong performance expectancy in terms of anticipated benefits.

Technopreneurship theory helps contextualise this inertia. Entrepreneurial alertness, defined as the capacity to identify and seize innovation opportunities, is critical for BMI through AIPaaS. Institutions embracing technopreneurial practices are more agile in piloting new platforms and adapting their models, often through cross-functional innovation labs or partnerships with fintech startups (Giones & Brem, 2017; Urban, 2017). These examples reinforce the importance of strategic vision and leadership in aligning AI adoption with business transformation goals.

Hypothesis 1 (H1): AIPaaS adoption positively influences business model innovation within Johannesburg's financial industry.

2.4.2 Dimensions of BMI

Artificial Intelligence Platform as a Service (AIPaaS) influences Business Model Innovation (BMI) across three critical and interrelated dimensions: value creation, value delivery, and value capture. These dimensions are consistent with established frameworks such as those proposed by Foss and Saebi (2017), who argue that successful BMI requires innovation not only in the development of new products or services, but also in the mechanisms through which value is delivered and monetised. Within Johannesburg's financial industry, each of these dimensions is affected differently by the application of AIPaaS technologies.

Value Creation: AIPaaS enables the design and deployment of novel products and services by using AI modelling and data-driven insights. This includes offerings like microloans tailored to informal entrepreneurs and insurance policies priced according to real-time behavioural data. These capabilities empower institutions to serve previously excluded or high-risk customer segments, thus expanding financial access. In the Johannesburg context, where socioeconomic disparities hinder traditional financial inclusion, these AI-enhanced solutions are not merely innovative—they are strategic imperatives (Motjolopane & Ruhode, 2022). The ability to harness structured and unstructured data for tailored financial products aligns with a

technopreneurial mindset, which encourages agile and opportunity-oriented approaches to solving entrenched problems (Urban, 2017).

Value Delivery: AIPaaS streamlines the way services are delivered to clients through automation and intelligent interfaces. Chatbots, voice assistants, and predictive engagement tools enhance the speed and quality of customer service, often replacing the need for physical interactions. Institutions like FNB and Nedbank have already implemented AI-driven interfaces that respond to client queries, deliver financial advice, and resolve service issues efficiently. This aligns with the Unified Theory of Acceptance and Use of Technology (UTAUT), particularly the construct of effort expectancy—clients perceive the system as useful and easy to use, fostering adoption and loyalty (Bianchi & Brière, 2022; Venkatesh et al., 2016).

Value Capture: AIPaaS offers financial institutions the opportunity to optimise cost structures and improve profitability by automating risk assessment, enhancing compliance monitoring, and minimising operational redundancies. Real-time analytics support dynamic pricing models, while fraud detection systems reduce exposure to financial loss. These improvements in cost efficiency and revenue control resonate with Mühlroth's (2020) notion of AI as an operational catalyst in data-intensive environments.

Together, these three dimensions showcase how AIPaaS can transform not only what financial institutions offer but also how they deliver and monetise those offerings—marking a fundamental shift in business model logic.

2.4.3 Comparative Analysis

A comparative lens offers meaningful insights into the state of AIPaaS adoption within Johannesburg's financial landscape when viewed alongside global benchmarks. Financial institutions in mature economies such as London, New York, and Singapore enjoy the advantage of advanced digital infrastructure, comprehensive AI policy frameworks, and a wealth of talent capable of building and sustaining complex AI systems. Institutions like HSBC use AI for real-time customer segmentation, while Citibank applies machine learning for dynamic portfolio management and fraud detection (Citigroup, 2024; HSBC Group, 2024).

These capabilities have not only enhanced efficiency and customer satisfaction but have also enabled rapid innovation cycles that keep these firms at the forefront of digital transformation.

In contrast, Johannesburg's financial institutions operate under a more constrained digital landscape. Legacy systems inhibit seamless data flow across departments, while regulatory complexity—particularly under South Africa's Protection of Personal Information Act (POPIA)—introduces delays in implementing AI tools due to strict data handling and compliance requirements. Furthermore, inconsistent levels of AI fluency among senior leaders limit strategic buy-in and hinder the ability to scale innovation. These constraints reflect the "facilitating conditions" and "social influence" constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT), which shape organisational readiness and user engagement (Venkatesh et al., 2016).

Despite these challenges, Johannesburg holds significant potential through its growing fintech ecosystem and increasingly vibrant innovation hubs. These dynamics present an opportunity for technopreneurial leadership to emerge. Drawing from technopreneurial theory, institutions can pursue "minimum viable AI" initiatives that encourage internal experimentation without requiring large-scale transformation from the outset (Masenya, 2021; Urban, 2017). Such initiatives might include low-risk AIPaaS pilot projects or strategic partnerships with Regtech startups that possess niche AI expertise. These collaborative efforts can reduce institutional resistance and stimulate innovation through knowledge transfer.

Moreover, regulatory innovation can further unlock AIPaaS's potential. The introduction of regulatory sandboxes—frameworks that permit controlled testing of innovative solutions within a defined legal boundary—has proved effective in fostering AI adoption in the UK and Singapore. Adapting similar models to the South African context could empower institutions to explore AIPaaS applications in a low-risk environment, encouraging proactive innovation while maintaining regulatory oversight (Javaid et al., 2022).

Johannesburg's financial institutions, though currently lagging global peers, are well-positioned to evolve into regional leaders in AI-driven innovation. Realising these potential hinges on a convergence of entrepreneurial leadership, strategic investment in digital infrastructure, and enabling policy mechanisms. AIPaaS adoption can become a catalyst for broader business model innovation—provided these systemic enablers are actively cultivated.

2.5 Innovation Dynamics

2.5.1 Organisational Adaptability

Organisational adaptability is a pivotal enabler of innovation, particularly in the financial services industry, where change is constant and technology adoption is mission-critical. It reflects an institution's ability to respond to external shifts—including technological disruptions, customer demands, and regulatory developments—through proactive strategies and structural flexibility (Budree & Gina, 2023; Urban & Maphumulo, 2022). The ability to adapt is especially pertinent to emerging economies like South Africa, where institutional rigidity often delays transformation.

Adaptability emerges in the UTAUT framework as part of "facilitating conditions," which determine the extent to which infrastructure and support mechanisms enable technology use (Venkatesh et al., 2016). Institutions that foster continuous professional development, empower adaptive leadership, and incorporate global best practices demonstrate higher readiness for AIPaaS integration. Johannesburg's financial industry exhibits varying degrees of adaptability, with larger banks such as FNB and Standard Bank showing greater maturity due to strategic investments in AI-readiness.

However, a key limitation remains the organisational inertia entrenched in hierarchical decision-making and siloed operations. Achmat (2023) reports that AI initiatives often lose momentum due to resistance from middle management, which prioritises risk mitigation over digital experimentation. Overcoming this requires technopreneurial leadership that sees disruption not as a threat but as an opportunity for reconfiguration.

Technopreneurship, as discussed by Giones and Brem (2017), calls for organisational agility driven by innovation-oriented decision-makers. Institutions must not only be technologically prepared but also strategically aligned to leverage AI as a vehicle for transformation. Thus, the following hypothesis is proposed:

Hypothesis 2 (H2): AIPaaS adoption positively affects organisational efficiency in Johannesburg's financial industry.

2.5.2 Innovation Culture

The internal culture of an organisation fundamentally shapes its openness to new technologies. Innovation culture refers to the shared beliefs, values, and norms that support experimentation, collaboration, and creative problem-solving (Foss & Saebi, 2017). It is the "social influence" component within UTAUT, where peer behaviours and leadership endorsement significantly affect technology acceptance.

Empirical evidence from Urban and Maphumulo (2021) reveals a strong correlation between innovation culture and successful AI implementation. In Johannesburg, institutions like Nedbank have embraced a culture of intrapreneurship, where employees are encouraged to propose and pilot AI-based solutions within business units. These initiatives exemplify how organisational culture translates into technological innovation.

Yet, fostering such a culture is not without its challenges. Many South African financial institutions continue to operate under conservative norms, where the fear of failure outweighs the drive for innovation. Overcoming this requires a deliberate shift in leadership mindset. Inclusive leadership—where cross-functional teams are engaged in ideation and strategic planning—has proven effective in embedding innovation into organisational DNA (Urban & Verachia, 2019).

Furthermore, this culture must extend beyond top management. Junior staff, operational teams, and compliance officers should also be involved in innovation processes. Such inclusivity not only enhances adoption outcomes but also builds institutional trust, critical in change-resistant environments. Technopreneurial leaders act as cultural architects, cultivating spaces where creativity is rewarded, and calculated risk-taking is supported.

2.5.3 Experimentation as a Driver of Innovation

Experimentation stands at the heart of innovation dynamics, especially when implementing emergent technologies like AIPaaS. It provides the mechanism through which organisations learn iteratively, reduce uncertainty, and refine their approaches (Giones & Brem, 2017). This aligns with entrepreneurial learning theory, which views innovation as an outcome of continuous trial, error, and adaptation.

In practice, experimentation manifests through pilot projects, prototyping, and sandbox environments. For instance, JP Morgan's pilot testing of AI for credit risk modelling illustrates how large-scale implementation is often preceded by low-risk experimental phases (J.P. Morgan Chase, 2023). Similarly, Standard Bank's internal AI lab in Johannesburg conducts iterative testing of chatbots and robo-advisors, demonstrating the value of experimentation in local contexts.

Despite its benefits, experimentation is often constrained in financial services due to regulatory rigidity and reputational risk. Institutions are hesitant to adopt a "fail-fast" mentality, fearing regulatory penalties and public backlash. However, regulatory sandboxes—controlled environments that permit limited trials of new technologies—offer a viable solution. Ryll et al. (2020) advocate for such frameworks, noting that they foster innovation without compromising compliance.

Johannesburg's regulatory authorities can play a transformative role by formalising sandbox structures, thereby lowering the barriers to experimentation. In turn, financial institutions can use these platforms to explore AIPaaS in applications like algorithmic underwriting or predictive customer segmentation without systemic risk.

2.5.4 Dynamics of Change Management

Successful AIPaaS adoption is not purely a technological challenge—it is fundamentally a human one. Change management, the structured process of transitioning individuals, teams, and organisations from a current state to a desired future state, is essential to mitigating resistance and embedding new practices (Murimbika & Urban, 2013).

Lewin's three-stage change model—unfreezing, moving, and refreezing—offers a practical framework for guiding organisations through transformation. Unfreezing involves challenging the status quo and preparing employees mentally and emotionally for change. This is particularly relevant in Johannesburg's financial institutions, where employees may perceive AI as a threat to job security or professional relevance.

The "moving" phase includes implementing AIPaaS with clear support structures, such as hands-on training, mentorship, and continuous feedback. Engagement from leadership during

this stage signals institutional commitment and reinforces the strategic value of the technology. Lastly, the "refreezing" phase institutionalises new behaviours through reward systems, role redefinition, and process integration (Mızrak, 2023).

Institutions that fail to manage these phases risk superficial adoption—where technologies are introduced but underutilised. Conversely, organisations that apply robust change management principles tend to witness higher technology utilisation rates and more positive staff attitudes towards AI (França, 2013).

Importantly, change management must be inclusive. Employees across departments—from IT to compliance—must be involved in the transformation journey. Communication, transparency, and empathy are critical success factors. Institutions that embrace these principles often find themselves with not just new tools, but a renewed organisational mindset capable of navigating ongoing digital disruption.

Hypothesis 2 (H2): AIPaaS adoption positively affects organisational efficiency in Johannesburg's financial industry.

2.6 Business Model Innovation Barriers

2.6.1 Technical Barriers

Technological impediments constitute some of the most immediate challenges in integrating AIPaaS within Johannesburg's financial institutions. The technopreneurial premise relies heavily on rapid iteration, data agility, and platform interoperability. However, these requirements are frequently undermined by concerns around data security and privacy (Deloitte, 2021). AIPaaS solutions typically necessitate access to large-scale, sensitive customer datasets—ranging from financial transactions to behavioural analytics—thereby increasing exposure to potential breaches.

Within the South African context, the enforcement of the Protection of Personal Information Act (POPIA) adds an additional layer of operational complexity (South African Government, 2021). For example, a financial entity deploying AIPaaS to refine credit scoring algorithms must ensure that both the data it gathers and the processing methods it uses comply with POPIA provisions. This involves securing informed consent, employing stringent storage protocols, and providing audit trails. Non-compliance, even if inadvertent, risks severe penalties and

reputational damage, which further disincentivises bold technological shifts (Slazus & Bick, 2022).

Beyond compliance, the structural limitations of legacy IT systems continue to pose significant technical hurdles. Many Johannesburg-based financial institutions operate within ecosystems developed well before the advent of AI platforms. These legacy infrastructures are often fragmented, with siloed databases and outdated middleware, making them incompatible with cloud-native AIPaaS solutions (Ernst & Young, 2023). Consequently, integration requires not only technical overhauls but also strategic patience.

Incremental modernisation strategies offer a feasible pathway through this challenge. Ernst & Young (2024) advocates hybrid integration models, where AIPaaS tools are deployed in parallel with legacy systems to test use-case viability before full-scale adoption. In practice, a Johannesburg bank might initially introduce AIPaaS to handle discrete operations—such as regulatory reporting or anti-money laundering protocols—while progressively upgrading foundational systems.

2.6.2 Organisational and Structural Barriers

Technopreneurship also requires institutional agility—an ability to make swift, coordinated decisions across complex organisational structures. However, the bureaucratic architecture of many financial institutions in Johannesburg works counter to this imperative. In hierarchical settings, the path from conceptualising an AI initiative to its implementation is often fraught with procedural inertia (Ajigini & Chinamasa, 2023). For example, a proposal to use AIPaaS for enhancing customer experience may linger in committee reviews and budgetary negotiations for months, during which the competitive context or technological landscape may shift considerably.

A related barrier lies in the compliance-innovation paradox. Regulatory compliance, while essential, often diverts internal resources away from innovation. In practice, compliance departments may be fully preoccupied with aligning internal operations with POPIA or Basel III frameworks, leaving minimal bandwidth to engage meaningfully in the design and execution of AIPaaS initiatives. This disproportionate allocation of institutional attention and expertise can stifle technopreneurial experimentation and dilute innovation pipelines.

Further exacerbating these challenges are organisational silos. AIPaaS deployment necessitates close collaboration between technical teams, compliance officers, operational staff, and front-line service units. However, siloed departments rarely align their priorities or timelines. An IT department may design an AIPaaS integration roadmap without sufficient input from legal teams, leading to unforeseen compliance violations (Ophoff & Miller, 2019). Similarly, frontline staff may resist the rollout of AI-driven customer engagement tools, perceiving them as disruptive or threatening to established workflows.

The literature on innovation management underscores the importance of cross-functional collaboration in overcoming such barriers. Urban (2017), for example, advocates the formation of integrated project teams that bring together multiple departments around shared goals. A Johannesburg-based bank aiming to introduce an AIPaaS tool for fraud detection might establish a cross-departmental working group—comprising representatives from compliance, customer service, risk, and IT—to ensure regulatory alignment, usability, and strategic coherence. Such collaborative platforms not only facilitate knowledge exchange but also increase the legitimacy of the innovation process within the institution.

Cultural resistance remains an often-overlooked but deeply entrenched barrier. Employees entrenched in analogue systems may view AI solutions as existential threats rather than tools for augmentation. For instance, customer service representatives might oppose the implementation of AIPaaS chatbots due to fears of redundancy or dehumanisation of service interactions. Overcoming this resistance requires more than technical training; it demands the cultivation of a digital-first mindset. Transparent communication, participatory design processes, and strong executive sponsorship are all critical to achieving this transformation.

Global examples provide instructive parallels. Citibank, for instance, successfully navigated internal resistance during its AI rollout by deploying a “champion network” across departments. These champions acted as internal advocates, offering peer support and serving as intermediaries between executive leadership and operational teams (Deloitte, 2021). Johannesburg-based institutions could adapt similar models, tailored to their own organisational cultures, to facilitate smoother transitions.

2.6.3 Perceived Costs and ROI Concerns

From a technopreneurship perspective, the economic viability of AIPaaS is a central concern. Despite the long-term efficiency gains AI tools promise, the short-term costs—platform acquisition, staff retraining, system upgrades—can appear prohibitive. Moreover, the intangible nature of some AIPaaS benefits, such as enhanced customer insights or predictive risk modelling, complicates traditional return on investment (ROI) calculations. Mulaudzi (2020) and Slazus and Bick (2022) note that many financial institutions either lack the metrics or the methodological tools to accurately quantify AIPaaS's impact on performance.

This misalignment between cost perception and strategic value frequently results in hesitancy or partial adoption. Decision-makers tend to prioritise visible, immediate expenditures over latent, distributed gains. Yet, the literature consistently points to the long-term advantages of AI integration in financial services, including reduced fraud, improved client retention, and streamlined operations (Foss & Saebi, 2018).

One possible intervention lies in benchmarking. Showcasing case studies from similar markets, where AIPaaS implementation has demonstrably improved key performance indicators, may recalibrate internal expectations. A Johannesburg-based firm considering AIPaaS for risk management might benefit from reviewing quantitative results from peers in Nairobi or Lagos that have experienced similar socio-economic and regulatory conditions. This comparative evidence can support more informed investment decisions.

2.6.4 Regulatory and Compliance Challenges

Regulatory uncertainty often constrains technopreneurial ambition. While the primary intent of regulations such as POPIA is to protect consumers and ensure ethical data usage, their interpretation and application frequently generate operational ambiguity. For technopreneurs, this creates a double bind: innovate too slowly and fall behind; innovate too quickly and risk non-compliance.

In contrast, regulatory regimes in other financial centres have adopted more enabling frameworks. Both London and Singapore have introduced regulatory sandboxes—controlled environments where institutions can test AI applications without full regulatory exposure.

These initiatives allow for iterative learning and controlled risk-taking, aligning well with the technopreneurial ethos of trial, error, and adaptation (Singapore Government, 2024).

Establishing similar mechanisms in Johannesburg could catalyse AIPaaS experimentation. Furthermore, stronger collaboration between regulators and industry actors is essential. Joint task forces or advisory panels could help align regulatory objectives with innovation agendas, making the compliance landscape more navigable. David (2020) argues that innovation and regulation need not be adversarial; rather, they can be co-constructed through ongoing dialogue and shared problem-solving.

2.7 Future Outlook

2.7.1 Addressing Barriers Through Technological Advancements

The persistent barriers to Artificial Intelligence Platform as a Service (AIPaaS) adoption in Johannesburg's financial industry—ranging from technological complexities to organisational inertia—require strategic foresight and innovative interventions. The continuous evolution of AIPaaS, underpinned by machine learning (ML), natural language processing (NLP), and cloud-native architectures, presents novel pathways for overcoming these limitations. Shahid and Sheikh (2021) advocate for a hybrid integration strategy, whereby AIPaaS tools operate alongside legacy systems. This phased approach enables financial institutions to modernise incrementally without disrupting ongoing operations or alienating existing stakeholders.

From a technopreneurship perspective, these advancements demand a reconfiguration of internal processes, culture, and leadership styles. Technopreneurs—entrepreneurial actors leveraging advanced technology to drive innovation—must act as change agents within traditionally risk-averse institutions (Ndou, 2004). AIPaaS-driven innovations are particularly effective in reengineering compliance and risk-management workflows. For instance, predictive analytics streamline regulatory adherence by automating documentation aligned with legislation such as the Protection of Personal Information Act (POPIA). Such digital efficiencies translate into lower compliance costs and faster go-to-market times for new products.

NLP-powered applications also hold promise for Johannesburg's multilingual financial ecosystem. As Khakhu (2023) observes, deploying AI chatbots in multiple South African

languages enhances accessibility and customer retention. This capacity to scale engagement while reducing operating costs reinforces arguments made by Urban (2017) about the transformative power of innovation-oriented cultures within firms. A crucial enabling condition is managerial buy-in, which is frequently hindered by uncertainties around return on investment (ROI). Foss and Saebi (2017) note that robust pilot programmes, supported by empirical case studies, are key to demonstrating both operational viability and strategic value.

Externally, regulatory innovation through mechanisms such as regulatory sandboxes can catalyse sector-wide adoption. Regulatory sandboxes allow financial service providers to test AIPaaS applications within supervised environments, balancing innovation with risk mitigation. Experiences from global hubs such as Singapore and London indicate that these mechanisms not only accelerate innovation but also provide valuable data for refining regulatory frameworks (Javaid et al., 2022). The Financial Sector Conduct Authority (FSCA) in South Africa could benefit from institutionalising similar programmes to align policy and innovation objectives.

2.7.2 Implications for Business Model Innovation

The integration of AIPaaS into financial operations in Johannesburg has profound implications for Business Model Innovation (BMI), particularly in how institutions create, deliver, and capture value. AIPaaS enables the real-time processing of behavioural analytics, thus facilitating hyper-personalisation of services. Dynamic credit scoring models and context-specific insurance offerings are becoming viable, especially in underserved or marginalised segments of the economy (Sjödin et al., 2021). Such approaches advance financial inclusion, a developmental imperative in South Africa's dual economy, while fostering sustainable competitive advantage.

The nexus of AIPaaS and blockchain technology also represents a forward-looking frontier in BMI. Blockchain provides a secure, immutable layer for transactional data, enabling trust-based models for decentralised finance (DeFi). In Johannesburg, this could facilitate secure, low-cost cross-border payments and support the development of regional financial products that account for local volatility, informality, and infrastructural gaps. Corporate actors such as HSBC and J.P. Morgan have already deployed AI-integrated blockchain solutions to improve transaction speed, cost, and transparency (HSBC Group, 2024; J.P. Morgan Chase, 2023).

These innovations suggest a roadmap for Johannesburg-based institutions seeking to expand regionally while maintaining compliance and agility.

Johannesburg's financial institutions must embed entrepreneurial capabilities across all organisational levels to unlock the full potential of AIPaaS. This requires institutional frameworks that promote experimentation, tolerate failure, and reward innovation outcomes. Urban (2017) highlights that cross-functional collaboration—particularly among IT, compliance, operations, and customer experience units—enhances alignment and speeds up learning cycles.

Establishing dedicated AI task forces or innovation labs can support institutional adaptation. These task forces should be mandated to scan emerging technologies, assess feasibility, and facilitate pilot projects with clear metrics. Drawing from Foss and Saebi (2017), strategic ambidexterity—the simultaneous pursuit of exploitation (efficiency) and exploration (innovation)—is essential for organisations navigating technological uncertainty.

2.7.3 Futurist Considerations and Strategic Direction

Looking ahead, the convergence of AIPaaS with quantum computing, 6G telecommunications, and even 10G as of late as well decentralised AI agents is likely to redefine the financial services landscape within the next decade. Institutions that fail to embed adaptive capacities now may find themselves structurally obsolete. Future-ready firms will be those that integrate environmental scanning into strategic planning, embrace algorithmic decision-making, and develop governance structures that are transparent, responsive, and technologically literate.

Moreover, Johannesburg's financial industry must engage with broader socio-political questions regarding data ethics, digital sovereignty, and algorithmic accountability. Technopreneurs and corporate entrepreneurs will play a crucial role in shaping ethical, inclusive innovation ecosystems. A futurist orientation requires not only technological adoption but also critical engagement with how technologies reconfigure power, access, and equity.

2.8 Chapter Summary

his chapter critically examined the factors influencing the adoption of Artificial Intelligence Platform as a Service (AIPaaS) within Johannesburg's financial industry, with a focus on its potential to drive business model innovation, enhance organisational efficiency, and support long-term competitiveness. The analysis was underpinned by four intersecting theoretical lenses: the Unified Theory of Acceptance and Use of Technology (UTAUT), Corporate Entrepreneurship, Technopreneurship, and Business Model Innovation (BMI).

Technopreneurship was positioned as the central framework through which the entrepreneurial utilisation of advanced technologies—particularly AI—was assessed in relation to organisational transformation. The study found that technopreneurial behaviours, such as experimentation, opportunity recognition, and risk tolerance, were critical enablers of AIPaaS adoption. These behaviours align with the broader innovation mandates of corporate entrepreneurship, which emphasise strategic renewal, cross-functional collaboration, and internal ventures as mechanisms for sustaining competitive advantage.

The UTAUT framework provided insight into the behavioural and perceptual factors shaping adoption intentions, highlighting the roles of performance expectancy, effort expectancy, social influence, and facilitating conditions. Notably, perceived usefulness and ease of integration influenced stakeholder receptivity, while the presence of organisational silos, outdated infrastructure, and resistance to change constrained adoption.

The chapter also demonstrated that business model innovation—defined as the reconfiguration of value creation, delivery, and capture mechanisms—was both a driver and outcome of AIPaaS integration. Institutions engaging in BMI leveraged AIPaaS capabilities to introduce personalised financial products, automate compliance, and enhance customer experiences. However, such transformation requires an internal culture that supports innovation, incentivises change, and aligns technological strategy with broader institutional objectives.

Context-specific barriers, such as regulatory uncertainty, limited technical skills, and constrained financial resources, were found to inhibit Johannesburg's financial institutions from fully capitalising on AIPaaS. Nevertheless, emerging technologies—such as predictive analytics, blockchain integration, and natural language processing—offer strategic pathways

for overcoming these barriers, especially when deployed within innovation-enabling environments like regulatory sandboxes.

Ultimately, the chapter established a foundational understanding of the dynamics shaping AIPaaS adoption within Johannesburg's financial ecosystem. It situated this adoption within a broader discourse of technopreneurial transformation, entrepreneurial renewal, and business model reconfiguration. These insights guide the study's subsequent empirical and analytical investigations into how AIPaaS can serve as both a technological and strategic lever for innovation-driven growth in the financial industry.

The next chapter outlines the study's methodological approach, detailing the research design, data collection methods, and analytical procedures adopted to investigate these dynamics.

Chapter 3: Research Methodology

3.1 Introduction

This chapter details the research methodology employed to investigate the adoption of Artificial Intelligence Platform as a Service (AIPaaS) within Johannesburg's financial industry. The methodology aligns with the study's objectives to explore perceptions, barriers, and opportunities for AIPaaS-driven business model innovation (BMI), ensuring a systematic approach to data collection, analysis, and interpretation.

The research design adopted a quantitative framework, leveraging measurable data to assess AIPaaS adoption among three key participant groups: decision-makers, AI/data specialists, and compliance officers. A structured survey methodology, administered via Qualtrics, provided a standardised data collection process while preserving participant anonymity. Advanced statistical tools, including SPSS and JASP, ensured the integrity of data analysis, with JASP functioning as a secondary tool to cross-verify SPSS outputs and enhance the reliability of the findings. This dual-software approach reinforced the study's commitment to methodological precision.

The study encountered challenges unique to its context. Low familiarity with AIPaaS among South African financial professionals was a notable limitation. While South Africa's financial system is globally competitive in terms of infrastructure and innovation capacity, its adoption of advanced AI platforms remains limited (Gladysz et al., 2023). This gap necessitated the inclusion of detailed contextual information and practical examples during data collection to facilitate participant understanding and ensure informed responses.

Another challenge was the hesitancy of financial institutions to share information regarding internal AI initiatives. Concerns about data security, competitive sensitivities, and compliance with the Protection of Personal Information Act (POPIA) often limited transparency. To address these concerns, the study implemented rigorous ethical protocols, guaranteeing confidentiality and adherence to POPIA while emphasising the broader industry benefits of participation. These measures fostered trust, enabling access to meaningful data while upholding ethical standards.

Through these methodological strategies, this chapter establishes a solid framework for exploring AIPaaS adoption, combining academic rigour with practical adaptability to address the complexities of studying emerging technology within Johannesburg's regulated financial landscape.

3.2 Research Design

3.2.1 Approach

This research adopted a quantitative design to assess measurable perceptions, challenges, and strategic opportunities surrounding the adoption of Artificial Intelligence Platform as a Service (AIPaaS) in Johannesburg's financial industry. Quantitative methods were selected for their ability to identify and analyse statistical relationships between key variables, particularly the link between organisational views of AIPaaS and its influence on business model innovation (BMI) (Creswell & Creswell, 2017). The design supports the study's dual aim: contributing to theoretical discourse while offering insights relevant to practice within a localised context.

A structured survey served as the core data collection tool, developed and distributed using Qualtrics. This platform was chosen due to its secure data management features and alignment with the data protection requirements of South Africa's Protection of Personal Information Act (POPIA). The survey included both 7-point Likert-scale items to gather quantitative responses and open-ended items to gather qualitative context (Leech et al., 2013). This design enabled the study to extract structured data while still recognising the complexity inherent in organisational change and technology adoption.

Data analysis was undertaken using SPSS and JASP to ensure analytical consistency and validation. SPSS provided the foundation for descriptive statistics, reliability checks, and regression analysis, while JASP was used to cross-verify the results and support advanced visual representation for exploratory factor analysis (EFA). Using two platforms strengthened the accuracy and dependability of the results.

The research design integrated validated survey constructs such as perceptions of AIPaaS (Q5–Q9) and BMI impact (Q10–Q13). These constructs were informed by frameworks like the Unified Theory of Acceptance and Use of Technology (UTAUT) and business model innovation literature, ensuring alignment with the study's core hypotheses and objectives.

3.2.2 Population and Scope

The research focused on professionals operating within Johannesburg's financial system, with particular attention paid to banking institutions. Banks were prioritised because of their influential role in driving financial innovation and digital transformation in South Africa. To extend relevance across the financial landscape, participants also included individuals from related financial domains, such as insurance and investment.

Three professional groups were targeted to ensure a comprehensive viewpoint:

1. **Decision-Makers:** Senior managers involved in shaping organisational strategy and investment in emerging technologies. This group offered insight into institutional goals and cost-benefit considerations of adopting AIPaaS.
2. **AI/Data Specialists:** Technically inclined professionals managing AI systems and data infrastructure. Their input helped clarify the operational feasibility and limitations of AIPaaS solutions.
3. **Compliance Officers:** Individuals responsible for ensuring regulatory adherence and data governance. Their responses addressed legal and ethical concerns, especially in relation to POPIA.

These groups brought complementary perspectives, reflecting the multifaceted considerations involved in adopting AI technologies.

Despite the study's broad scope, certain challenges were encountered. Awareness of AIPaaS among participants remained limited, a reflection of the early stage of AI integration in South African financial institutions (Slazus & Bick, 2022). o address this, the survey incorporated brief descriptions and contextual clarifications to guide participants. Moreover, institutions displayed reluctance in sharing internal insights about AI initiatives, primarily due to concerns about confidentiality. Reassurances regarding anonymity and the broader academic purpose of the study were used to encourage participation.

3.2.3 Sampling Dynamics

A hybrid sampling approach was used, combining convenience and snowball techniques. Initially, participants were selected based on their accessibility within known financial

institutions, helping to overcome logistical constraints. Thereafter, referrals from those participants helped expand the sample across professional networks.

This approach proved particularly useful given the restricted access often encountered in highly regulated financial environments. However, one limitation of this method lies in the potential for selection bias. Respondents recruited through personal or professional links may represent similar institutional cultures or viewpoints. To reduce this effect, care was taken to ensure a diverse mix of professional roles and participation across multiple financial domains, such as banking, insurance, and asset management.

Through this hybrid method, the study succeeded in collecting perspectives from a broad range of participants, contributing to a balanced understanding of the organisational, technical, and regulatory issues shaping AIPaaS adoption in Johannesburg's financial landscape.

3.3 Sampling Technique

3.3.1 Sampling Strategy

The study utilised a pragmatic convenience sampling strategy to recruit professionals within Johannesburg's financial industry, with a particular emphasis on banking institutions. This method facilitated timely access to participants within a tightly regulated and strategically sensitive environment where conventional probabilistic sampling approaches may have proven impractical (Field, 2018). Initial contact was made through professional and academic circles, leveraging known affiliations to secure participation among decision-makers, compliance officers, and technical specialists.

Participant recruitment was further expanded through a snowball sampling effect. Individuals who had completed the survey recommended it to colleagues within their professional networks, broadening the participant base beyond the initial focus group. This approach enriched the dataset by introducing participants from a wider range of financial organisations, including insurance and asset management. Combining convenience and snowball sampling supported the capture of diverse perspectives while remaining feasible within the constraints of the study's timeline and context.

Despite its benefits, convenience sampling does introduce limitations, particularly the risk of homogeneity due to shared networks and institutional affiliations. To mitigate this, efforts were made to ensure variation in participant roles and organisational backgrounds. The inclusion of the three predefined professional roles—decision-makers, AI/data specialists, and compliance officers—further contributed to the balance and depth of the data collected.

3.3.2 Sample Size

An initial sample size of 180 respondents was targeted to ensure statistical robustness across subgroups. However, limitations surrounding awareness of AIPaaS and organisational hesitancies regarding participation led to a reduced final dataset. After data cleaning, which involved excluding incomplete or invalid entries, 82 valid responses were retained for analysis.

Though smaller than anticipated, this sample proved sufficient for the study's analytical needs. The dataset met the minimum thresholds for regression and factor analysis, as supported by methodological guidelines (Field, 2018; Pallant, 2021). Moreover, its diversity across strategic, technical, and regulatory roles enabled meaningful examination of the relationships between perceptions, barriers, and the adoption of AIPaaS.

3.4 Data Collection Process

3.4.1 Survey Instrument

Data collection was conducted using Qualtrics, a secure and academically recognised platform selected for its alignment with data protection protocols, including South Africa's Protection of Personal Information Act (POPIA) (Douglas et al., 2023). The instrument was designed to gather both structured and open-ended responses, ensuring comprehensive insights into AIPaaS adoption.

The survey comprised:

- **Likert-scale items**: Designed to measure perceptions, readiness, innovation orientation, and perceived barriers to AIPaaS. These items enabled statistical testing of relationships between constructs aligned with the research hypotheses.
- **Open-ended questions**: These provided qualitative depth, capturing strategic reflections and contextual realities that numeric data might obscure.

Survey constructs were grounded in existing literature. For instance, items measuring perceived usefulness and organisational readiness were adapted from Venkatesh et al. (2016), ensuring theoretical congruence. A detailed breakdown of each construct and its corresponding items is provided in the Descriptive Testing and Construct Analysis Table (Appendices, Table A.1).

3.4.2 Administration

Survey administration occurred in two waves:

- **Initial Targeted Distribution**: Outreach was first directed to professionals in the banking space using professional and academic networks. Familiarity with the researcher or project appeared instrumental in securing responses, particularly in roles where sensitivity to organisational data is high.
- **Snowball Referral Phase**: The second wave saw increased distribution via referrals, particularly through mid-level managers and specialists who circulated the survey to peers across institutions. This approach increased representation from adjacent areas, including insurance and fintech.

Challenges during data collection included low engagement from senior-level professionals due to time constraints and general unfamiliarity with AIPaaS. Institutional risk aversion also limited the scope of internal insights. These constraints were partially addressed through a simplified survey layout, time-efficient design, and assurances of anonymity and ethical compliance.

3.4.3 Ethical Considerations

Ethical compliance was a critical component of the data collection process due to the study's engagement with sensitive topics, including technological adoption and institutional decision-making. Anonymity and confidentiality were rigorously maintained to uphold international standards for research ethics and ensure adherence to South Africa's Protection of Personal Information Act (POPIA) (Bryman, 2016; Clark et al., 2021). Qualtrics, the platform used to administer the survey, was selected for its encrypted data handling and secure storage, reinforcing compliance with local data protection requirements.

Participants were informed about the study's aims and provided electronic consent before proceeding. This consent process clearly outlined the voluntary nature of participation, the

option to withdraw without penalty, and the confidentiality measures in place (Bryman, 2016). In foregrounding transparency, the study built trust with respondents, which was essential given the institutional sensitivities surrounding artificial intelligence and digital transformation in financial services. (Bryman, 2016).

3.5 Ethics Clearance Process

The study was conducted in strict adherence to ethical standards to protect participants and ensure institutional compliance. Ethical approval was granted by the **University of the Witwatersrand Ethics Review Board** after a thorough evaluation of the research proposal, including its objectives, methodology, and participant protection strategies. The ethics clearance certificate (Ethics Protocol Number: WBS/EN681632/174) is included in the appendix as a reference, underscoring the research's credibility and alignment with established ethical guidelines.

Compliance with POPIA

A cornerstone of the ethical framework was compliance with **South Africa's Protection of Personal Information Act (POPIA)**, which governs the responsible collection, storage, and use of personal data. To minimise risks and uphold privacy, the study deliberately avoided collecting sensitive personal data, such as participant identifiers or financial records. Key measures implemented to comply with POPIA included:

- **Encrypted Responses**: Participant responses were encrypted during data collection and storage, ensuring their protection against breaches.
- **Secure Storage**: The dataset was securely stored on Qualtrics, a platform known for its robust compliance with international data security standards (Bryman, 2016; South African Government, 2021).

These precautions safeguarded participant information, demonstrating a commitment to maintaining confidentiality and security

Building Participant Trust

Given the sensitive nature of AIPaaS adoption—particularly its implications for organisational competitiveness—initial hesitations were observed among participants. Ethical clearance was instrumental in addressing these concerns, providing assurances about the study's adherence

to rigorous ethical standards. Participants were informed that their anonymity would be preserved, with no personally identifiable information collected or shared.

Transparent communication played a key role in fostering trust. The study's objectives, methods, and potential contributions to industry knowledge were clearly explained, reinforcing its legitimacy. Participants were further assured of their right to withdraw at any point, a critical element of the informed consent process (Clark et al., 2021).

Institutional Cooperation

The ethical clearance process also facilitated cooperation with financial institutions. Organisations were more inclined to support the research knowing it adhered to established ethical standards. This cooperation was vital for accessing a diverse participant pool and enriching the study's dataset.

Through a robust ethical framework encompassing POPIA compliance, clear communication, and institutional approval, the study ensured both the protection of participants and the credibility of its findings. These measures not only addressed the unique challenges of researching AI adoption in a sensitive and competitive industry but also set a benchmark for ethical conduct in future studies (Bryman, 2016).

3.6 Data Cleaning and Preparation

3.6.1 Data Cleaning

The initial dataset contained 83 responses, which were systematically evaluated to ensure reliability and completeness. One response with over 10% missing data was excluded through **listwise deletion**, a standard practice to maintain dataset integrity and prevent bias in statistical analysis (Field, 2018; Pallant, 2021). For responses with minor missing values, the **replace missing values process** was applied to compute replacements, preserving the robustness of the dataset without compromising its validity.

Outlier Management

Outliers were identified using boxplot analysis to detect responses that significantly deviated from the general data distribution (Leech et al., 2013). Rather than removing these anomalies, they were retained as they represented legitimate variations in participant perspectives. For

instance, compliance officers, whose responses often focus on regulatory challenges, naturally differed from the innovation-driven inputs of AI/data specialists. Including these outliers ensured a comprehensive representation of diverse viewpoints, enriching the dataset and providing nuanced insights.

3.6.2 Preparation for Analysis

The cleaned dataset was prepared for analysis using SPSS and JASP, selected for their robust capabilities in statistical testing and validation (McBride & Garcés-Manzanera, 2024). The preparation process involved meticulous steps to enhance data quality:

- **Variable Consistency**: Variables were clearly labelled and standardised to ensure consistency across tools. Each construct, such as AIPaaS Perceptions and BMI Impact, was assigned interpretable labels to minimise errors during analysis.
- **Verification for Completeness**: The dataset underwent thorough checks to confirm that all data points were present and accurately recorded. This step ensured that the analyses adhered to best practices in quantitative research, reducing the risk of incomplete or erroneous outputs (Leech et al., 2013).

Alignment with Analytical Requirements

The prepared dataset aligned seamlessly with the analytical frameworks outlined in the research design, facilitating the application of advanced statistical methods such as regression and exploratory factor analysis. The dual-use of SPSS and JASP enhanced the reliability of findings, as outputs were cross-validated to identify and resolve any discrepancies.

In maintaining a meticulous approach to data cleaning and preparation, the study ensured the accuracy, validity, and reliability of its analyses, laying a robust foundation for meaningful insights into AIPaaS adoption in Johannesburg's financial industry.

3.7 Data Analysis Tools

Data analysis for this study was structured around validated constructs aligned with the research objectives and hypotheses. Constructs such as Business Model Innovation and Innovation Dynamics were operationalised through specific survey items designed to capture perceptions, barriers, and strategic outcomes of AIPaaS adoption within Johannesburg's financial industry (Creswell & Creswell, 2017). This design ensured both theoretical relevance and analytical coherence.

SPSS was used as the main analytical tool due to its capacity to process complex datasets and run diverse statistical tests (Field, 2018). Descriptive statistics were first produced to summarise demographic patterns and identify general trends within the dataset. Cronbach's alpha was then applied to assess the internal consistency of multi-item constructs, confirming the reliability of variables such as perceived usefulness and organisational resistance (Tavakol & Dennick, 2011; Pallant, 2021). Subsequent regression and correlation analyses examined relationships between AIPaaS perceptions and key outcomes such as innovation and operational efficiency.

While the study initially followed traditional statistical testing methods, it became evident that the dynamic and emerging nature of AIPaaS demanded a more adaptive analytical strategy. Exploratory Factor Analysis (EFA), a common validation tool, revealed limitations in its ability to explain construct behaviours within this evolving context (Shrestha, 2021). In response, the study adopted a construct-led approach, focusing analysis around theoretical groupings rather than relying solely on EFA to define variable structures. This pivot was necessary given the lack of precedent and theoretical grounding in the South African financial landscape.

To enhance the transparency and accuracy of the findings, JASP was used to visually confirm key results through factor loading diagrams and scree plots. These visuals supported SPSS outputs and helped validate the coherence of constructs like Innovation Dynamics (McBride & Garcés-Manzanera, 2024). The integration of SPSS and JASP not only improved methodological robustness but also reflected the analytical adaptability needed in under-researched domains such as AIPaaS.

3.8 Methodological Challenges

3.8.1 Limited Familiarity with AIPaaS

A central challenge emerged around limited familiarity with AIPaaS among participants. As an emergent digital infrastructure in South Africa's financial industry, AIPaaS remains underutilised and underexplored. Participants—particularly those outside data-specialist roles—often lacked conceptual clarity, which impacted how they engaged with survey constructs (Li & Ding, 2024). To mitigate this, the survey included contextual prompts and embedded definitions relevant to the financial industry, such as AI-enabled fraud detection and

algorithmic credit scoring. These clarifications were essential to enable informed responses and enhance data reliability.

3.8.2 Institutional Sensitivities

Concerns about confidentiality and data sharing emerged as significant barriers, especially in light of stringent data governance under South Africa's Protection of Personal Information Act (POPIA). Respondents from banking institutions were particularly cautious about revealing insights into internal AI practices. To address this, the study incorporated a clear ethical protocol including anonymised responses, encrypted data handling, and informed consent (Bryman, 2016; Clark et al., 2021; South African Government, 2021). Framing the study as an academic inquiry with practical value for industry development helped to position participation as low-risk and mutually beneficial.

3.8.3 Participant Engagement and Methodological Adaptation

A further challenge involved sustaining meaningful engagement from professionals operating within high-pressure environments. A number of participants, particularly those in senior roles such as decision-makers and compliance officers, faced significant time constraints that affected their ability to complete the survey in full. Although the combination of convenience sampling and snowball referrals broadened access, this approach did not fully mitigate the issue of limited availability. As a result, while participation was diverse, the depth and consistency of responses varied across roles.

In addition to logistical constraints, the study encountered an important epistemological consideration. Although the research design was framed as quantitative—allowing for statistical exploration of relationships between AIPaaS perceptions, innovation dynamics, and business model outcomes—the nature of the topic and the behaviour of the data revealed the limitations of a purely numerical approach. The complexity of how institutions conceptualise and engage with AIPaaS, especially in a nascent and fluid technological domain, pointed to the potential value of integrating qualitative dimensions. For instance, open-ended responses often revealed nuance and context that could not be captured through Likert-scale items alone.

This realisation, which emerged during the analytic phase, highlighted a methodological tension. While quantitative methods provided structured, measurable outputs, certain

interpretive insights—such as how organisational culture influences resistance to AI—were better suited to qualitative inquiry. Though the study did not formally adopt a mixed methods design, the experience affirmed the importance of methodological flexibility when investigating emerging, under-theorised phenomena. This limitation not only informed the interpretive lens through which quantitative findings were analysed but also offered a useful direction for future research aiming to build a more holistic understanding of AIPaaS adoption.

3.9 Justification of Methodology

The methodology aligns closely with the study's objectives, using a quantitative research design to investigate perceptions, barriers, and opportunities surrounding Artificial Intelligence Platform as a Service (AIPaaS) adoption in Johannesburg's financial industry. Convenience sampling, supplemented by a snowball effect, facilitated access to diverse roles, including decision-makers, AI/data specialists, and compliance officers, ensuring a multidimensional dataset reflective of strategic, technical, and regulatory perspectives.

SPSS and JASP ensured analytical rigor, with SPSS conducting core analyses and JASP validating outputs and enhancing interpretability. Ethical compliance with South Africa's Protection of Personal Information Act (POPIA) safeguarded participant data through anonymisation, secure storage, and informed consent processes.
This framework effectively addressed the study's objectives, balancing statistical precision with contextual relevance to produce credible, actionable insights.

3.10 Chapter Summary

This chapter presented the research methodology adopted to examine the adoption of Artificial Intelligence Platform as a Service (AIPaaS) within Johannesburg's financial industry. It outlined the rationale for a quantitative research design aimed at capturing measurable insights into perceptions, organisational barriers, and strategic opportunities. Structured surveys were distributed using the Qualtrics platform, which offered a secure and compliant environment in accordance with South Africa's Protection of Personal Information Act (POPIA).

A hybrid sampling approach—combining convenience with snowball sampling—enabled access to a range of professionals, including decision-makers, AI/data specialists, and compliance officers. This diversity allowed the study to reflect the strategic, technical, and

regulatory perspectives central to AIPaaS implementation. Challenges such as unfamiliarity with the technology and institutional hesitation were addressed through tailored survey communication, anonymisation protocols, and clear contextual guidance within the instrument.

Data analysis was carried out using SPSS and JASP. SPSS supported core statistical testing, while JASP validated outputs and contributed visual clarity through exploratory factor analysis and residual diagnostics. Data cleaning measures—including the removal of invalid responses and consideration of outliers—reinforced the reliability of the dataset.

Ethical safeguards were embedded throughout the study design. Participant anonymity, informed consent, and secure data handling procedures were prioritised, ensuring both regulatory compliance and participant confidence. These elements were essential in navigating the financial industry's regulatory sensitivities and promoting engagement.

Ultimately, this chapter established the methodological foundation for the study's analytical work in Chapter 4. The alignment between research objectives, analytical tools, and contextual realities strengthens the credibility of the findings and their contribution to understanding AIPaaS adoption and business model innovation in South Africa's financial landscape.

Chapter 4: Data Analysis, Results, and Interpretation

4.1 Introduction

This chapter presents a detailed analysis of data collected from South Africa's financial industry, focusing on the adoption of Artificial Intelligence Platform as a Service (AIPaaS) and its impact on business model innovation (BMI) and operational efficiency. The findings are derived from various statistical methods, including descriptive statistics, reliability analysis, exploratory factor analysis (EFA), correlation analysis, regression analysis, and ANOVA. These methods were carefully chosen to align with the study's objectives and ensure robust and rigorous analysis.

The chapter aims to explore the dynamics of AIPaaS adoption across key organisational roles—decision-makers, compliance officers, and AI/data specialists—emphasising how these roles shape perceptions and influence BMI outcomes. The insights provide a nuanced understanding of AIPaaS's strategic value while acknowledging the unique challenges and opportunities it presents within South Africa's financial landscape. To complement the quantitative findings, qualitative responses were analysed thematically, offering deeper insights into participant perspectives.

Analytical procedures adhered to established academic guidelines, ensuring the validity, reliability, and transparency of results. Thru employing diverse analytical techniques, this chapter builds a comprehensive understanding of the research problem, aligning with best practices for integrating quantitative and qualitative methodologies to enhance the depth of findings (Field, 2018).

The chapter is structured to systematically present the methodologies, results, and interpretations for each type of analysis. This structured approach lays the foundation for Chapter 5, where the findings will be contextualised to provide practical recommendations and implications for Johannesburg's financial institutions.

4.2 Data Cleaning and Handling

Data cleaning plays a crucial role in quantitative research, establishing a solid foundation for credible and replicable findings. The initial dataset consisted of 83 responses, with one

excluded due to missing data exceeding 10% of survey items. Listwise deletion, widely recommended in quantitative analysis literature (Field, 2018; Pallant, 2021), was applied to ensure only complete cases were retained. This approach reduced the dataset to 82 valid responses, effectively minimising the risk of biased estimates that incomplete data might introduce.

Potential outliers were identified through a boxplot analysis. These outliers, representing legitimate variations in participant perspectives, were retained. Their inclusion reflects the diverse roles of respondents—decision-makers, compliance officers, and AI/data specialists—and aligns with the study's objective to capture nuanced perceptions of AIPaaS across organisational functions. Acknowledging such variability ensures the dataset remains representative of the dynamic and often divergent views within companies.

Maintaining these diverse perspectives reinforces the study's aim of exploring the interplay between role-based responsibilities and perceptions of AIPaaS. Pallant (2021) highlights the value of retaining legitimate outliers, particularly when analysing heterogeneous groups. This methodological choice underlines the importance of contextual considerations in achieving meaningful quantitative research outcomes.

Note to Reader: Rationale for Construct-Level Analysis

Although the initial exploratory factor analysis yielded two strong factor loadings that jointly explained 83.23% of the variance—suggesting considerable internal alignment among the items—this study opted for construct-level analysis rather than aggregating the dimensions. The rationale for this approach, grounded in both methodological rigour and theoretical clarity, is outlined below. *(Refer to Exploratory Factor Analysis - Initial Loadings for supporting evidence)*

Reliability Testing: Each construct was subjected to reliability testing using Cronbach's Alpha to assess internal consistency. The results, with values ranging from 0.929 to 0.971, demonstrated that all constructs were both statistically robust and conceptually coherent. These high scores validated the integrity of each dimension, supporting their independent use in subsequent analyses.

Facilitation of Correlation and Regression Analysis: The decision to treat constructs independently enabled a more nuanced examination of the relationships among variables through correlation and regression analysis. This disaggregated approach allowed the study

to capture the distinct influence of constructs such as AIPaaS Perceptions, Innovation Dynamics, BMI Impact Metrics, Barriers, and Future Outlook. By isolating these elements, the analysis could trace their specific contributions to business model innovation and organisational efficiency, rather than relying on composite scores that may obscure such dynamics.

Theoretical Alignment: This approach aligns with established methodological principles that emphasise the importance of analysing individual constructs to identify their differentiated impact on dependent outcomes (Field, 2018; Pallant, 2021). Notably, the novelty of this research—centred on AIPaaS adoption in Johannesburg's financial services industry—required a departure from conventional statistical heuristics. Applying standardised models without accounting for contextual specificity would have introduced epistemic and ideological biases, diminishing the theoretical integrity of the analysis. Construct-level evaluation ensured that the findings reflected the empirical complexity and contextual sensitivity that the topic demands.

Practical Relevance: From a practical perspective, treating each construct separately enhances the strategic utility of the findings. For instance, recognising that perceptions of AIPaaS influence business model innovation differently than infrastructural or cultural barriers allows stakeholders to develop targeted responses. Such specificity would be lost in aggregated analyses, which often fail to distinguish between conceptually discrete but practically significant factors.

In sum, the choice to maintain construct-level distinctions—despite strong initial factor loadings—was driven by both theoretical necessity and empirical clarity. This approach enhanced the validity, reliability, and applicability of the findings, ensuring they remain context-sensitive, methodologically sound, and practically relevant for advancing understanding of AIPaaS adoption and business model innovation in Johannesburg's financial services industry.

4.3 Descriptive Statistics

4.3.1 Participant Demographics

Descriptive statistics summarised key demographic characteristics, providing foundational insights into the dataset. Participants were distributed evenly across three roles: decision-makers (32.9%), compliance officers (32.9%), and AI/data specialists (34.1%) within the 82

valid cases for the study, as illustrated in Figure 2. This balanced representation captures a diverse range of organisational perspectives, aligning with the study's objective of examining role-specific attitudes toward AIPaaS adoption.



Figure 2 Participant Demographics by Professional Role

Industry affiliation data indicated that banking services accounted for the largest proportion of participants (31.7%), followed by insurance (18.3%) and wealth management (17.1%). These findings align with the dominant role of banking and insurance in driving innovation within South Africa's financial landscape (Urban & Naidoo, 2012). Gender distribution was nearly equal, with male participants at 43.9% and female participants at 48.8%. However, participation rates for individuals not identifying within these two categories were notably low. See Figure 3 for additional details.

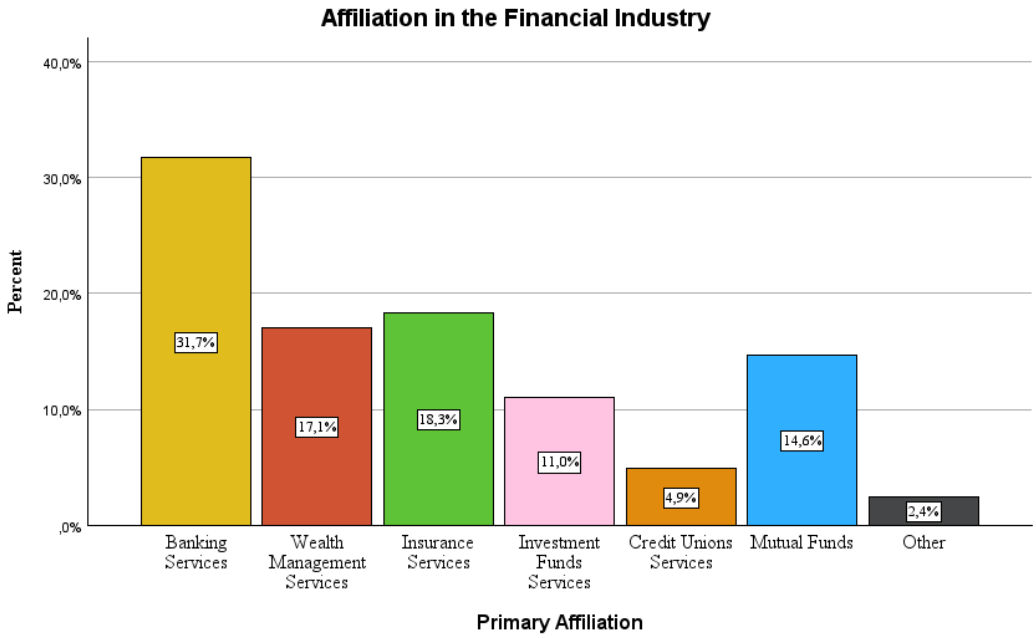


Figure 3 Industry Affiliation of Survey Respondents

4.3.2 Measures of Central Tendency and Dispersion

The Likert-scale constructs, used to measure perceptions of AIPaaS (Q5–Q9) and BMI metrics (Q10–Q13), revealed valuable patterns in participant responses:

- **Mean Scores:** Perceptions of AIPaaS usefulness (M = 2.09) and familiarity (M = 2.89) reflect moderate agreement, indicating general awareness of AIPaaS with variability in its perceived impact.
- **Standard Deviations:** The effectiveness of AIPaaS received varied responses, with a standard deviation of 1.319 for Q7, reflecting diverse opinions consistent with the heterogeneity of participant roles.

These descriptive statistics emphasise the importance of contextualising AIPaaS adoption within specific organisational roles and industry contexts. The findings reinforce previous studies on technology adoption in emerging markets, highlighting the nuanced perspectives of different stakeholder groups (Venkatesh et al., 2016).

4.4 Reliability Analysis (Cronbach's Alpha)

Purpose

The reliability analysis aimed to evaluate whether the multi-item constructs consistently measured their intended concepts. Cronbach's Alpha served as the reliability coefficient, with

values above 0.7 considered acceptable and values exceeding 0.9 regarded as excellent (Tavakol & Dennick, 2011). To enhance the analysis, inter-item correlations were reviewed to confirm the cohesion and internal consistency of the survey items.

Table 1 Reliability Statistics and Inter-Item Correlations

Construct	Cronbach's Alpha	Standardised Cronbach's Alpha	Items	Inter-Item Correlation (Range)
AIPaaS Perception (Q5–Q9)	0.943	0.948	5	Strong (e.g., Q6–Q8: 0.932)
AIPaaS BMI Impact Metrics (Q10–Q13)	0.971	0.971	4	High (e.g., Q12–Q13: 0.931)
AIPaaS Innovation Dynamics (Q14–Q18)	0.956	0.955	5	High (0.632–0.952)
AIPaaS Barriers (Q19–Q23)	0.929	0.931	5	Moderate to High (0.603–0.834)
AIPaaS Future Outlook (Q24–Q26)	0.962	0.967	3	Strong (0.895–0.926)

Findings

- *AIPaaS Perception (Q5–Q9)*
  Cronbach's Alpha of 0.943 indicated excellent reliability. Inter-item correlations, such as Q6–Q8 (0.932), confirmed strong internal cohesion.
- *AIPaaS BMI Impact Metrics (Q10–Q13)*
  Cronbach's Alpha of 0.971 reflected outstanding consistency, with high inter-item correlations (e.g., Q12–Q13: 0.931) validating reliability.
- *AIPaaS Innovation Dynamics (Q14–Q18)*
  Cronbach's Alpha of 0.956 confirmed excellent reliability. Inter-item correlations ranged from 0.632 to 0.952, with strong associations between Q16–Q18.
- *AIPaaS Barriers (Q19–Q23)*
  Cronbach's Alpha of 0.929 demonstrated high reliability. Inter-item correlations (0.603–0.834) indicated consistent relationships among the items.
- *AIPaaS Future Outlook (Q24–Q26)*

Cronbach's Alpha of 0.962 indicated exceptional reliability, with strong inter-item correlations ranging from 0.895 to 0.926.

Interpretation

The reliability analysis confirmed that all constructs within the survey instrument demonstrated excellent internal consistency, with Cronbach's Alpha values exceeding the 0.9 threshold.

- Strong inter-item correlations for AIPaaS Perception and Future Outlook validated the cohesive measurement of these constructs.
- Moderate-to-strong correlations in AIPaaS Barriers highlighted some variability in responses while maintaining acceptable reliability.
- Consistently high correlations in AIPaaS Innovation Dynamics and BMI Impact Metrics validated the precision of these constructs in capturing their intended concepts.

These findings support the use of composite scores in subsequent factor analysis and regression modelling, ensuring that the constructs reliably represent participants' perceptions and experiences of AIPaaS adoption and its impact on business model innovation. The results align with Tavakol and Dennick (2011), affirming the robustness of the survey instrument for academic and practical applications.

4.5 Exploratory Factor Analysis (EFA)

Purpose

The purpose of the Exploratory Factor Analysis (EFA) was to validate the internal structure of the survey constructs and ensure that the items within each dimension align statistically. This method evaluates unidimensionality by determining whether items under a construct measure a single underlying factor (Field, 2018; Pallant, 2021). Confirming unidimensionality strengthens the integrity of constructs for subsequent analyses, including regression and correlation models.

Table 2 Exploratory Factor Analysis (EFA) Summary

Construct	KMO Value	Bartlett's Test (χ^2, df, Sig.)	Variance Explained (%)	Key Notes
AIPaaS Perceptions (Q5–Q9)	0.874	$\chi^2 = 449.145$, df = 10, $p < 0.001$	83.08%	Strong item loadings (e.g., Q6 = 0.967).
BMI Impact Metrics (Q10–Q13)	0.854	$\chi^2 = 502.526$, df = 6, $p < 0.001$	92.16%	High variance, confirming unidimensionality.
Innovation Dynamics (Q14–Q18)	0.850	$\chi^2 = 551.210$, df = 10, $p < 0.001$	85.19%	Strong inter-item correlations observed.
AIPaaS Barriers (Q19–Q23)	0.878	$\chi^2 = 332.559$, df = 10, $p < 0.001$	78.52%	Adequate consistency across items.
Future Outlook (Q24–Q26)	0.778	$\chi^2 = 297.861$, df = 3, $p < 0.001$	93.81%	High item correlations (e.g., Q24–Q26).

Findings

The results of the EFA confirm strong unidimensionality across all five constructs, as summarised in **Table 2**:

- AIPaaS Perceptions (Q5–Q9):
  - KMO = 0.874, demonstrating excellent sampling adequacy.
  - Bartlett's Test ($\chi^2 = 449.145$, $p < 0.001$) validated strong inter-item correlations.
  - A single factor explained 83.08% of the variance, with strong loadings, such as Q6 (0.967) and Q8 (0.962).
- AIPaaS BMI Impact Metrics (Q10–Q13):
  - KMO = 0.854, reflecting excellent adequacy for factor analysis.
  - A single factor accounted for 92.16% of the variance, with high alignment among items reinforcing unidimensionality.
- AIPaaS Innovation Dynamics (Q14–Q18):
  - KMO = 0.850, indicating excellent suitability for EFA.
  - Variance explained was 85.19%, with strong inter-item correlations observed (e.g., Q16–Q18: 0.952–0.924).
- AIPaaS Barriers (Q19–Q23):

    - KMO = 0.878, the highest among constructs, confirming sampling adequacy.
    - Variance explained was 78.52%, with moderate-to-strong inter-item correlations validating consistency.
- AIPaaS Future Outlook (Q24–Q26):
    - KMO = 0.778, reflecting acceptable adequacy for factor analysis.
    - Variance explained was 93.81%, supported by high inter-item correlations (e.g., Q24–Q26: 0.926–0.900).

Interpretation

The EFA results confirmed unidimensionality for all constructs—AIPaaS Perceptions, BMI Impact Metrics, Innovation Dynamics, Barriers, and Future Outlook. Key findings include:

- High variance explained (78.52%–93.81%) for each construct, validating their focus on a single underlying factor.
- Strong KMO values (0.778–0.878), demonstrating the adequacy of the data for factor analysis.
- Significant Bartlett's Test results across constructs, confirming sufficient inter-item correlations for factor extraction.

These findings affirm the reliability and validity of the survey instrument, justifying the use of composite scores in advanced analyses such as regression and correlation models. The confirmed unidimensionality aligns with theoretical expectations, enabling precise measurement of participants' perceptions of AIPaaS adoption and its impact on business model innovation (BMI). The results adhere to best practices in factor analysis (Pallant, 2021; Shrestha, 2021), reinforcing the credibility of the research findings. *See results section with synthesised results.*

4.6 Correlation Analysis

Purpose

The correlation analysis assessed the strength and direction of relationships among key variables—AIPaaS_BMI, AIPaaS_Perceptions, AIPaaS_InnovationDynamics, and AIPaaS_Barriers. This analysis aimed to uncover significant associations that illuminate the dynamics driving business model innovation (BMI) within the context of AIPaaS adoption.

Findings

Strength of Correlations:

- AIPaaS_BMI:
    - Strong positive correlation with AIPaaS_Perceptions ($r = 0.909$, $p < 0.001$).
    - Strong positive correlation with AIPaaS_InnovationDynamics ($r = 0.886$, $p < 0.001$).
    - Moderate positive correlation with AIPaaS_Barriers ($r = 0.752$, $p < 0.001$).
- AIPaaS_Perceptions:
    - Strong positive correlation with AIPaaS_InnovationDynamics ($r = 0.906$, $p < 0.001$).
    - Moderate positive correlation with AIPaaS_Barriers ($r = 0.822$, $p < 0.001$).
- AIPaaS_InnovationDynamics:
        - Moderate positive correlation with AIPaaS_Barriers ($r = 0.811$, $p < 0.001$).

Statistical Significance:

- All correlations were statistically significant at $p < 0.001$, confirming the robustness of relationships among the variables.

Sample Size:

- The analysis included data from 82 participants for all variables, ensuring reliable and valid results.

Table 3 Pearson Correlation Matrix for AIPaaS Constructs

Variable	AIPaaS_BMI	AIPaaS_Perceptions	AIPaaS_InnovationDynamics	AIPaaS_Barriers
Pearson Correlation				
AIPaaS_BMI	1.000	0.909	0.886	0.752
AIPaaS_Perceptions	0.909	1.000	0.906	0.822
AIPaaS_Innovation Dynamics	0.886	0.906	1.000	0.811
AIPaaS_Barriers	0.752	0.822	0.811	1.000
Sig. (1-tailed)				
AIPaaS_BMI	.	<0.001	<0.001	<0.001
AIPaaS_Perceptions	<0.001	.	<0.001	<0.001
AIPaaS_Innovation Dynamics	<0.001	<0.001	.	<0.001
AIPaaS_Barriers	<0.001	<0.001	<0.001	.
N				
AIPaaS_BMI	82	82	82	82
AIPaaS_Perceptions	82	82	82	82
AIPaaS_Innovation Dynamics	82	82	82	82
AIPaaS_Barriers	82			82

Interpretation

Relationships with AIPaaS_BMI:

- AIPaaS_Perceptions exhibited the strongest relationship (r = 0.909), suggesting that positive perceptions of AIPaaS significantly enhance business model innovation. This finding aligns with research indicating that favourable perceptions drive readiness for technology adoption, leading to strategic improvements.
- AIPaaS_InnovationDynamics also showed a strong positive relationship (r = 0.886), emphasising the importance of fostering an innovation-driven culture to enable adaptive and experimental strategies that enhance business models.

- AIPaaS_Barriers demonstrated a moderate correlation (r = 0.752), suggesting that while barriers may impede adoption, they can also stimulate creative strategies to overcome challenges, indirectly fostering innovation.

Interrelationships Among Predictors:

- The strong correlation between AIPaaS_Perceptions and AIPaaS_InnovationDynamics (r = 0.906) highlights their interconnected roles. Positive perceptions appear to foster environments that support innovation, creating a reinforcing dynamic.
- Moderate correlations between AIPaaS_Barriers and both AIPaaS_Perceptions (r = 0.822) and AIPaaS_InnovationDynamics (r = 0.811) suggest that barriers may drive strategic problem-solving, enhancing perceptions and innovation readiness within organisations.

Holistic View:

- These results illustrate the complex dynamics of AIPaaS adoption. Positive perceptions and innovation dynamics act as critical enablers of BMI, while barriers, though moderate in their effect, emphasise the importance of organisational readiness and strategic adaptation. Addressing barriers alongside fostering positive perceptions and a culture of innovation is vital for realising the full potential of AIPaaS.

4.7 Regression Analysis

4.7.1a Simple Linear Regression

Purpose

This analysis explored the direct effect of AIPaaS Innovation Dynamics on Business Model Innovation (BMI). The construct was selected due to its pivotal role, evidenced by high loading scores in factor analysis. AIPaaS Innovation Dynamics encompasses adaptability, experimentation, and fostering an innovation-friendly culture, aligning closely with strategic drivers of BMI.

Findings

- The regression model explained 78.5% of the variance in BMI ($R^2 = 0.785$, $F(1, 80) = 292.803$, $p < 0.001$).

- The coefficient for AIPaaS Innovation Dynamics was significant (B = 1.072, β = 0.886, p < 0.001), indicating that a one-unit increase in innovation dynamics leads to a 1.072-unit increase in BMI.

Table 4 Model Summary for Linear Regression Examining AIPaaS Innovation Dynamics and BMI

R	R^2	Adjusted R^2	Std. Error of the Estimate	F	df1, df2	p
0.886	0.785	0.783	0.64037	292.803	1, 80	<0.001

Table 5 ANOVA Results for Regression Analysis Linking AIPaaS Innovation Dynamics to BMI

Source	Sum of Squares	df	Mean Square	F	p
Regression	120.072	1	120.072	292.803	<0.001
Residual	32.806	80	0.410		
Total	152.878	81			

Table 6 Coefficients Table for Linear Regression of AIPaaS Innovation Dynamics on BMI

Variable	B (Unstandardized Coefficient)	SE (Standard Error)	β (Standardized Coefficient)	t	p	95% Confidence Interval
(Constant)	0.043	0.157	-	0.273	0.786	[-0.270, 0.356]
AIPaaS Innovation Dynamics	1.072	0.063	0.886	17.111	<0.001	[0.947, 1.196]

Interpretation

The analysis stresses the critical role of AIPaaS Innovation Dynamics in driving BMI. The strong positive coefficient (B = 1.072, β = 0.886, p < 0.001) demonstrates that organisations with robust innovation dynamics achieve substantial improvements in BMI outcomes. The high R^2 value (0.785) confirms AIPaaS Innovation Dynamics as a dominant predictor, explaining nearly 79% of BMI variance. These findings are consistent with prior studies by Urban (2017) and Venkatesh et al. (2016), emphasising the importance of innovation culture, adaptability, and experimentation.

4.7.1b Simple Linear Regression

Purpose

This analysis examined the direct impact of AIPaaS Barriers on BMI. The construct was studied for its dual role as both a constraint and a driver of strategic innovation. Barriers such as data security concerns, compliance issues, and resistance to change often compel organisations to adapt and reconfigure business models to overcome challenges.

Findings

- The regression model explained 56.6% of the variance in BMI ($R^2 = 0.566$, $F(1, 80) = 104.137$, $p < 0.001$).
- The coefficient for AIPaaS Barriers was significant ($B = 0.856$, $\beta = 0.752$, $p < 0.001$), suggesting a one-unit increase in barriers corresponds to a 0.856-unit increase in BMI.

Table 7Model Summary for Linear Regression Examining AIPaaS Barriers and BMI

R	R^2	Adjusted R^2	Standard Error of the Estimate	F	df1, df2	p
0.752	0.566	0.560	0.91118	104.137	1, 80	<0.001

Table 8 ANOVA Results for Regression Analysis Linking AIPaaS Barriers to BMI

Source	Sum of Squares	df	Mean Square	F	p
Regression	86.459	1	86.459	104.137	<0.001
Residual	66.419	80	0.830		
Total	152.878	81			

Table 9 Coefficients Table for Linear Regression of AIPaaS Barriers on BMI

Variable	B (Unstandardized Coefficient)	SE (Standard Error)	β (Standardized Coefficient)	t	p	95% Confidence Interval
(Constant)	-0.572	0.312	-	-1.332	0.071	[-1.195, 0.051]
AIPaaS Barriers	0.856	0.084	0.752	10.205	<0.001	[0.689, 1.024]

Interpretation

AIPaaS Barriers demonstrated a significant positive relationship with BMI (B = 0.856, β = 0.752, $p < 0.001$). This finding suggests that barriers may act as strategic drivers for innovation, compelling organisations to reconfigure their business models. The R^2 value (0.566) indicates barriers explain over half the variance in BMI, consistent with theories on adaptive innovation (Urban, 2017; Murimbika & Urban, 2013).

4.7.2 Multiple Regression : Combined Effects of Predictors on BMI

Purpose

This analysis evaluated the combined effects of AIPaaS Perceptions, Innovation Dynamics, and Barriers on BMI. AIPaaS Perceptions and Innovation Dynamics were included due to their high factor loadings and shared theoretical influence, while Barriers were included as a distinct predictor of constraints.

Findings

Model 1:

- Included **AIPaaS Perceptions** and **AIPaaS Innovation Dynamics** as predictors.
- Explained **84.8% of the variance** in BMI ($R^2 = 0.848$, $F(2, 79) = 220.507$, $p < 0.001$).
- Both predictors were statistically significant:
  - **AIPaaS Perceptions**: B = 0.743, β = 0.592, $p < 0.001$.
  - **AIPaaS Innovation Dynamics**: B = 0.423, β = 0.350, p = 0.001.

Model 2:

- Added **AIPaaS Barriers** as a third predictor.
- Explained **84.9% of the variance** in BMI ($R^2 = 0.849$, $F(3, 78) = 146.430$, $p < 0.001$).

- Results for the predictors were as follows:
    - **AIPaaS Perceptions**: B = 0.786, β = 0.622, p < 0.001.
    - **AIPaaS Innovation Dynamics**: B = 0.413, β = 0.343, p = 0.001.
    - **AIPaaS Barriers**: B = -0.070, β = -0.061, p = 0.446 (not significant).

Table 10 Model Summary for Multiple Regression Analysis of AIPaaS Constructs Predicting BMI

Model	*R*	*R²*	*Adjusted R²*	*Standard Error of the Estimate*	*F*	*df1, df2*	*p*
Model 1	*0.921*	*0.848*	*0.843*	*0.54221*	*220.507*	*2, 79*	*<0.001*
Model 2	*0.922*	*0.849*	*0.843*	*0.54363*	*146.430*	*3, 78*	*<0.001*

Table 11 ANOVA Results for Multiple Regression Models Linking AIPaaS Constructs to BMI

Model	Source	Sum of Squares	df	Mean Square	F	p
Model 1	Regression	129,653	2	64,826	220.507	<0.001
	Residual	23,225	79	0.294		
	Total	152,878	81			
Model 2	Regression	129,826	3	43,275	146.430	<0.001
	Residual	23,052	78	0.296		
	Total	152,878	81			

Table 12 Coefficients Table for Multiple Regression Analysis of AIPaaS Constructs on BMI

Variable	B (Unstandardised Coefficient)	SE (Standard Error)	β (Standardised Coefficient)	t	p	95% Confidence Interval
(Constant)	*-0.194*	*0.191*	*-*	*-1.016*	*0.313*	*[-0.574, 0.186]*
Model 1						
AIPaaS Perceptions	*0.743*	*0.131*	*0.592*	*5.709*	*<0.001*	*[0.483, 1.003]*
AIPaaS Innovation Dynamics	*0.423*	*0.125*	*0.350*	*3.372*	*0.001*	*[0.175, 0.671]*
Model 2						
AIPaaS Perceptions	*0.786*	*0.141*	*0.622*	*5.595*	*<0.001*	*[0.505, 1.067]*
AIPaaS Innovation Dynamics	*0.413*	*0.125*	*0.343*	*3.295*	*0.001*	*[0.164, 0.662]*
AIPaaS Barriers	*-0.070*	*0.091*	*-0.061*	*-0.765*	*0.446*	*[-0.251, 0.111]*

Interpretation

The results demonstrate that AIPaaS Perceptions and AIPaaS Innovation Dynamics have significant positive effects on BMI, whereas AIPaaS Barriers are not statistically significant:

- AIPaaS Perceptions is the strongest predictor ($\beta = 0.622$, $p < 0.001$), confirming its critical role in enhancing business model innovation through positive technological perceptions.
- AIPaaS Innovation Dynamics also contributes significantly ($\beta = 0.343$, $p = 0.001$), reflecting the importance of adaptability and experimentation within organisations.
- AIPaaS Barriers ($\beta = -0.061$, $p = 0.446$) does not significantly influence BMI when perceptions and innovation dynamics are included in the model, suggesting its relative weakness as a predictor.

The incremental increase in R^2 from 0.848 to 0.849 AIPaaS Perceptions and Innovation Dynamics demonstrate significantly impact BMI, while Barriers exhibit limited additional influence when combined with the other predictors. These findings align with theoretical frameworks on technology adoption and organisational readiness, as discussed by Foss and Saebi (2017) and Venkatesh et al. (2016).

4.8 Thematic Analysis

Purpose

Thematic analysis was employed to complement the quantitative findings by examining open-ended responses from participants. This method aimed to uncover barriers and opportunities associated with AIPaaS adoption, providing nuanced insights into perceptions and experiences within South Africa's financial services industry.

Findings

- Barriers to AIPaaS Adoption
    - Data Security and Regulatory Compliance:

      Concerns regarding data privacy and insufficient regulatory frameworks were prevalent. Participants highlighted the cautious stance of organisations:

      > ***"We are cautiously optimistic about the potential of AI, but we need to ensure that we address compliance and regulatory issues, especially in an industry like ours."***
      > ***"We are still struggling on developing frameworks on how to regulate the system, and at this point, little change is happening in compliance regarding data and client privacy."***
    - Uncertainty and Scepticism:

      Doubts about the immediate transformative impact of AIPaaS were noted, with some participants viewing it as more of a trend than a proven tool:

      > ***"Too soon to tell if AIPaaS will 'revolutionise' the industry. Right now it feels more like a buzzword than a true effective tool."***
      > ***"I am not convinced it will change or has changed operations of mutual banks anytime soon."***

- Opportunities Identified

- Operational Efficiency:
  Participants widely acknowledged AIPaaS's potential to streamline workflows, optimise processes, and improve accuracy:

  > ***"AI is definitely impactful and has changed how we run our processes, more specifically rendering credit facilities at a higher rate and more accurately in credit profile assessment."***
  > ***"AI tools make things easier to do and faster than the bank did in the past."***

- Competitive Advantage and Future-Proofing:
  AIPaaS was recognised as a strategic tool for ensuring long-term success, enabling better data management and fostering innovation:

  > ***"The integration of AIPaaS is a no-brainer for modern-day banking. With better data management, we can streamline services more efficiently."***
  > ***"AI will benefit our system through future-proofing."***
  > ***"The possibilities of AI within the sector are beneficial because work has become easier, ensuring business processes flow well."***

Interpretation

The thematic analysis enhances the quantitative results by capturing participants' subjective experiences and perspectives on AIPaaS adoption. While the quantitative data underlines the strategic value of AIPaaS, qualitative insights provide a balanced view, revealing both optimism and caution.

Barriers such as concerns over data privacy and regulatory gaps highlight the pressing need for robust frameworks to ensure secure and compliant adoption. On the other hand, opportunities in operational efficiency, competitive advantage, and future-proofing demonstrate the tangible benefits of AIPaaS integration.

Participants expressed a cautious yet optimistic outlook, underscoring the importance of aligning organisational strategies with regulatory developments. As one participant aptly summarised:

> ***"We are cautiously optimistic about AI, but the regulatory environment must catch up before we can fully embrace its potential."***

4.9 Chapter Summary

This chapter examined the influence of Artificial Intelligence Platform as a Service (AIPaaS) on business model innovation (BMI) and organisational efficiency within Johannesburg's financial services industry. Descriptive statistics highlighted variations in awareness and engagement across roles, emphasising the need for tailored, role-specific strategies.

Reliability analysis confirmed the strong internal consistency of the constructs, with Cronbach's Alpha scores ranging from 0.929 to 0.971. Exploratory Factor Analysis (EFA) further validated the constructs' unidimensionality, supported by high KMO values and significant Bartlett's Tests, ensuring robust measurement reliability.

Correlation and regression analyses demonstrated that AIPaaS Perceptions and Innovation Dynamics are critical predictors of BMI. These findings pointed out the strategic importance of fostering positive perceptions and cultivating innovation-friendly cultures. Barriers such as regulatory compliance and data privacy concerns were identified as both constraints and catalysts for adaptive strategies, highlighting the dual role of challenges in driving organisational innovation.

Thematic analysis enriched the quantitative results by providing qualitative insights into participants' experiences. While practical challenges such as regulatory misalignment and uncertainty about AIPaaS's transformative potential were evident, the opportunities—improved customer engagement, operational efficiency, and future-proofing—illustrated the tangible benefits of adoption. Participants emphasised the need for alignment with frameworks like the Protection of Personal Information Act (POPIA) to facilitate secure and compliant integration.

These findings provide a comprehensive understanding of the opportunities and challenges associated with AIPaaS adoption, laying the groundwork for the next chapter. The following section will outline strategic recommendations to enhance adoption, address identified barriers, and maximise the transformative potential of AIPaaS within Johannesburg's financial services industry.

Chapter 5: Discussion and Recommendations

5.1 Introduction

This chapter interprets the findings from Chapter 4 in the context of the theoretical and practical frameworks established in Chapters 2 and 3. It offers a structured discussion that aligns the results with the study's objectives and hypotheses, focusing on the influence of Artificial Intelligence Platform as a Service (AIPaaS) on business model innovation (BMI) and organisational efficiency in Johannesburg's financial services industry.

The discussion begins with an analysis of key findings, evaluated against existing literature and theoretical models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and business model frameworks. This approach underlines the alignment and differences between the findings and global research on AI adoption in emerging markets, offering a deeper interpretation.

The next section presents actionable recommendations to address the challenges identified in the study, including regulatory hurdles, organisational resistance, and concerns over data security. These recommendations are tailored to key stakeholders such as industry leaders, policymakers, and researchers to ensure relevance and practicality for Johannesburg's financial institutions.

The chapter concludes by reflecting on the broader implications of the findings for the financial ecosystem. This final section highlights the strategic role of AIPaaS in driving operational and innovative transformations while encouraging further exploration of the study's insights. This structure integrates empirical results with practical guidance for a well-rounded understanding of the research outcomes.

5.2 Discussion of Findings

5.2.1 Overview of Key Findings:

The findings in Chapter 4 provided a detailed examination of perceptions, impacts, and challenges surrounding Artificial Intelligence Platform as a Service (AIPaaS) adoption within Johannesburg's financial industry. They offered insight into the complexities of integrating advanced AI technologies in a highly regulated environment.

Awareness of AIPaaS varied significantly, with AI/data specialists showing higher familiarity than compliance officers and decision-makers. This disparity indicates uneven dissemination of knowledge within organisations, impacting readiness for adoption.

A strong positive correlation was observed between AIPaaS adoption and business model innovation (BMI), affirming its role as a driver for enhancing product offerings, customer engagement, and operational efficiency. Regression analyses further supported the hypothesis that perceived usefulness of AIPaaS positively influences organisational efficiency. AIPaaS's ability to streamline workflows, optimise resource allocation, and reduce costs emerged as critical benefits (Ernst & Young, 2024c, 2024d).

Barriers to adoption were also identified, including technical challenges like legacy systems and compliance with the Protection of Personal Information Act (POPIA). Organisational resistance compounded these issues, with cultural inertia and fear of disruption hindering scalability (Liu et al., 2024).

These findings align with global research, which also highlights technical limitations and regulatory hurdles as common obstacles to AI adoption. However, Johannesburg's context introduces heightened concerns over data privacy and uneven awareness across roles, underscoring the need for tailored interventions.

*The findings validated Hypothesis 1 (H1): **AIPaaS adoption positively influences business model innovation within Johannesburg's financial services industry**. The data demonstrates that AIPaaS enables the development of innovative products, enhances customer engagement, and optimises operational processes, thereby aligning with global research findings.*

*Similarly, the analysis supported Hypothesis 2 (H2): **AIPaaS adoption positively affects organisational efficiency**. The study revealed significant improvements in operational workflows, automation, and resource optimisation, highlighting AIPaaS's role in enhancing organisational performance.*

5.2.2 Perceptions of AIPaaS Adoption

Awareness and Familiarity

Participants' awareness of AIPaaS varied significantly across professional roles, with AI/data specialists and decision-makers generally more informed than compliance officers. Decision-makers, who are typically involved in strategic planning, demonstrated a broader understanding of AIPaaS's capabilities and implementation complexities, reflecting their exposure to global technological trends. In contrast, compliance officers expressed limited awareness, citing a lack of targeted training and organisational communication as contributing factors (Ashraf & Atasi, 2022).

Globally, awareness of AI technologies has grown steadily, driven by increased investment in education and outreach by leading technology firms such as Amazon Web Services and Microsoft (Amazon Web Services, 2024; Microsoft, 2023).However, this trend has not fully permeated Johannesburg's financial industry. The findings revealed that while larger institutions displayed greater familiarity with AIPaaS, smaller organisations, particularly within the insurance subindustry, lagged in awareness. This gap highlights the need for industry-wide initiatives to enhance knowledge sharing and training, ensuring all stakeholders are equipped to engage with AIPaaS effectively (Ashraf & Atasi, 2022). Such efforts would ensure that all stakeholders, regardless of organisational size or role, are equipped to understand and engage with AIPaaS effectively.

Perceived Usefulness and Effectiveness

Participants across all roles acknowledged the potential benefits of AIPaaS, particularly in improving operational efficiency and driving innovation. Decision-makers viewed AIPaaS as a strategic tool for streamlining workflows and enhancing customer engagement. For instance, AI-powered platforms were seen as instrumental in enabling personalised financial products tailored to customer needs, a competitive advantage in a highly dynamic industry (Bautzer & Nguyen, 2023; Deloitte, 2021; Forbes Finance, 2024). Compliance officers, while less familiar with AIPaaS, recognised its potential to simplify regulatory reporting. These professionals highlighted the platform's ability to automate repetitive tasks, reduce human error, and improve accuracy, particularly in environments governed by complex regulatory frameworks like POPIA. Data specialists, on the other hand, emphasised the platform's capability to manage large datasets efficiently, enabling real-time insights and predictive analytics (Mossavar

Rahmani, 2023; Rashid & Kausik, 2024). This functionality was seen as essential for identifying trends, mitigating risks, and supporting evidence-based decision-making.

Role-specific perceptions highlighted differing priorities: decision-makers focused on AIPaaS's role in driving BMI, while compliance officers valued its capacity to simplify compliance processes. These distinctions highlight the importance of role-tailored implementation strategies.

Challenges in Perception

Despite recognising its benefits, participants expressed scepticism about AIPaaS adoption, often rooted in concerns about technological disruption and cost implications. Organisational hierarchy played a significant role in shaping these perceptions. Senior executives were more likely to advocate for AIPaaS, viewing it as essential for maintaining competitiveness. In contrast, mid-level managers and employees, particularly in compliance roles, were cautious, citing fears of job displacement and increased workloads during implementation.

Organisational culture also emerged as a critical factor. Institutions with a strong culture of innovation exhibited more positive perceptions of AIPaaS, seeing it as an opportunity to enhance their competitive edge. These organisations were characterised by proactive leadership, cross-departmental collaboration, and a willingness to invest in experimental technologies. Conversely, conservative organisations were less enthusiastic, exhibiting lower enthusiasm for AIPaaS adoption. Employees in these settings often viewed AIPaaS as a disruptive force rather than an enabler of growth.

These findings align with existing literature, which highlights the role of leadership and culture in shaping technology adoption (Urban, 2017; Urban & Maphumulo, 2022). They also underline the need for targeted interventions to address scepticism and resistance, such as transparent communication from leadership about the strategic benefits of AIPaaS and training programs to demystify the technology and its implications (Budree & Gina, 2023; Murimbika & Urban, 2013).

5.2.3 Impact on Business Model Innovation

AIPaaS as a Driver of BMI

The findings highlighted AIPaaS as a pivotal enabler of BMI, fostering innovation in product development, customer engagement, and operational efficiency (Citigroup, 2024; Sjödin et al., 2021). Examples include dynamic loan products targeting underserved markets and behaviour-based insurance leveraging real-time data. These applications demonstrate AIPaaS's role in reshaping value creation and delivery.

Compared to global benchmarks, Johannesburg's financial institutions are in the early stages of leveraging AIPaaS for BMI. While institutions in developed markets, such as JP Morgan and Mastercard, have integrated AI-driven platforms into their core operations which has impacted their product offerings, operational efficiency, and customer interactions, Johannesburg's firms often rely on pilot projects or limited-scale implementations (Achmat, 2023; Price Waterhouse Coopers, 2024). This disparity highlights the need for strategic investments in AIPaaS to close the innovation gap. Institutions must prioritise not only the adoption of AI technologies but also the development of the necessary infrastructure, expertise, and culture to support their integration. Such investments would position Johannesburg's financial industry to fully leverage the capabilities of AIPaaS, aligning it more closely with global best practices in BMI.

These findings confirm Hypothesis 1 (H1), demonstrating that AIPaaS adoption serves as a critical enabler of business model innovation by transforming value creation, delivery, and capture mechanisms. The study's evidence highlights AIPaaS's ability to address local market challenges while aligning Johannesburg's financial industry with global innovation trends.

Dimensions of BMI

The study identified three key dimensions of BMI facilitated by AIPaaS:

- *Value Creation:* value delivery, and value capture. In value creation, AIPaaS enabled institutions to design products that meet diverse customer needs, such as flexible credit solutions for small businesses (Forbes Finance, 2024). For instance, flexible credit solutions for small businesses were enabled through AI-driven analytics, providing tailored financial support based on individual business profiles. These capabilities address a significant gap in Johannesburg's financial ecosystem, where traditional models often fail to accommodate the unique needs of smaller enterprises (Motjolopane & Ruhode, 2022).

- *Value Delivery:* AI-driven platforms enhanced customer interactions through personalised services, including real-time financial advice and automated customer support, providing personalised services that align with global trends in customer-centric innovation. Banks, in particular, demonstrated significant progress in this dimension, leveraging AI to create seamless and interactive customer experiences (Bautzer & Nguyen, 2023).
- *Value capture:* AIPaaS improved profitability by optimising pricing models and reducing operational costs. For example, advanced predictive algorithms facilitated more accurate risk assessments, enabling institutions to adjust pricing strategies dynamically. Additionally, automation of routine processes reduced overheads, freeing up resources for strategic initiatives (Mühlroth, 2020). All of the three dimensions are similarly represented in the study through questions i) Impact on Product/Service Offerings, ii) Impact on Customer Experience, and iii) Impact on Operational Efficiency.

Industrial differences also emerged, reflecting the unique priorities and challenges with banks demonstrating greater innovation in value delivery, prioritising on customer engagement and retention, while insurance firms focused on value creation through personalised product offerings. These variations reflect the unique priorities and competitive pressures within each subindustry.

5.2.4 Organisational Efficiency

Efficiency Gains through AIPaaS

AIPaaS adoption significantly improved workflows, particularly in compliance, fraud detection, and customer service. Automated compliance tools streamlined regulatory reporting, while fraud detection systems enhanced accuracy and response times, minimising losses (Standard Bank South Africa, 2024).

Customer service benefited from AI-driven chatbots, which improved query resolution and reduced wait times. These tools allowed human resources to focus on strategic tasks, further enhancing efficiency.

Pre-AIPaaS processes were often semi-manual and error-prone; AIPaaS adoption streamlined workflows, enabling more effective resource allocation and strategic focus (Pandey &

Sergeeva, 2022). This shift represents a significant step toward operational excellence, positioning Johannesburg's financial institutions to compete more effectively on a global scale.

The findings strongly support Hypothesis 2 (H2), which proposed that AIPaaS adoption positively affects organisational efficiency. Improvements in compliance, fraud detection, and customer service highlight AIPaaS's transformative impact, reducing costs and enhancing accuracy in Johannesburg's financial institutions.

Barriers to Efficiency Gains

Despite these improvements, technical barriers, such as legacy systems and data integration challenges, limiting the full realisation of efficiency gains. Many institutions struggled to integrate AIPaaS with existing infrastructure, leading to delays and increased implementation costs. creating a bottleneck for widespread adoption.

Organisational resistance also emerged as a significant barrier, particularly among employees concerned about job displacement and increased workloads during the transition. These fears, coupled with a lack of transparency and communication from leadership, created resistance that hindered adoption efforts. Mid-level managers and operational staff were particularly cautious, often viewing AIPaaS as a potential disruptor rather than an enabler of efficiency.
Resource constraints further compounded these challenges. Smaller institutions, in particular, lack the financial and technical capacity to implement AIPaaS at scale, reinforcing disparities within the industry.

Addressing these barriers requires a multifaceted approach. Institutions must invest in upgrading infrastructure, streamlining data integration processes, and fostering a culture of openness and adaptability. Leadership plays a critical role in mitigating resistance by clearly communicating the benefits of AIPaaS, providing training programs, and offering reassurances about job security. Policymakers can also support these efforts by providing incentives and resources to help smaller institutions overcome financial and technical constraints.

5.2.5 Barriers to AIPaaS Adoption

Technical Barriers

Technical challenges, including data security concerns and outdated infrastructure, were among the most significant barriers to AIPaaS adoption. Participants highlighted the risks associated with handling sensitive customer data, particularly under South Africa's POPIA framework. These concerns often delayed adoption, as institutions prioritised compliance over innovation.

Legacy systems posed another critical challenge. Many organisations relied on outdated technologies that were incompatible with AIPaaS, requiring costly upgrades before integration could proceed. These findings are consistent with global research, which identifies legacy infrastructure as a common barrier to AI adoption (Ernst & Young, 2023).

Regulatory and Organisational Barriers

While AIPaaS simplifies compliance processes, uncertainty regarding its regulatory alignment delayed adoption. Organisational barriers such as silos and bureaucratic inertia hindered collaboration, slowing decision-making and implementation (Liu et al., 2024).

Addressing the Barriers

Strategies included:

- **Targeted Training:** Equip employees with skills to manage AIPaaS technologies.
- **Incremental Implementation:** Phased approaches to mitigate disruption.
- **Partnerships:** Collaborate with technology providers for smoother integration.

5.2.6 Future Outlook

Potential for Scaling AIPaaS Adoption

Emerging trends in AI technology, such as improved scalability and enhanced data processing capabilities, present significant opportunities for scaling AIPaaS adoption. Participants highlighted the potential for collaboration between banks, fintech firms, and policymakers to create an ecosystem conducive to innovation. For example, shared AI platforms could facilitate real-time fraud detection across the industry, enhancing efficiency and security.

Policy interventions, including tax incentives for AI investments and streamlined regulations, were identified as critical for accelerating adoption and integration into Johannesburg's financial ecosystem.

5.3 Recommendations

5.3.1 Strategic Recommendations for Practitioners

Awareness and Education

Increasing awareness and understanding of AIPaaS among financial professionals is crucial for advancing adoption within Johannesburg's financial industry. Chapter 4 highlighted notable disparities in familiarity, particularly between decision-makers and compliance officers. Bridging this gap requires a targeted educational approach to ensure informed decision-making at all organisational levels.

Industry-wide workshops and forums can showcase AIPaaS capabilities through practical case studies and live demonstrations, such as examples of AI-powered fraud detection reducing financial losses or dynamic loan products tailored using AI analytics. Engagement from local and international experts can provide best practices tailored to Johannesburg's financial ecosystem.

Executive training programs, tailored for decision-makers, can align AIPaaS adoption with organisational strategy, focusing on return on investment (ROI) and long-term benefits. Partnerships between academic institutions and technology providers can ensure these programs are grounded in evidence-based insights and real-world applications.

Online educational platforms, developed in collaboration with leading technology providers, can complement in-person initiatives. Interactive e-learning resources and certification programs could incentivise participation, equipping professionals as AIPaaS ambassadors within their organisations.

Fostering Innovation Culture

The success of AIPaaS adoption hinges on an organisation's innovation culture. Findings revealed that institutions with strong innovation cultures were more receptive to AIPaaS, while conservative organisations resisted. Leadership must cultivate a culture that prioritises adaptability, experimentation, and collaboration.

Senior executives should integrate AIPaaS into strategic goals, communicating its role in driving innovation and efficiency to motivate employees. Cross-functional innovation teams, including representatives from compliance, IT, operations, and strategy, can collaboratively identify applications of AIPaaS, such as AI-driven compliance monitoring to reduce workloads and ensure legal adherence.

Rewarding employee-driven innovation can embed AIPaaS into organisational culture. Recognising employees who propose creative uses for AIPaaS, such as predictive analytics for personalised customer engagement, reinforces proactive participation. Incentives like financial rewards, professional development opportunities, or public acknowledgment can further encourage such initiatives.

Optimising Data Security and Compliance

Addressing data security and compliance concerns requires proactive strategies. Financial institutions should implement advanced encryption and privacy-enhancing technologies, such as anonymisation, to secure sensitive customer data. End-to-end encryption can safeguard information during transmission and storage, ensuring compliance with the Protection of Personal Information Act (POPIA).

Regular data security audits can identify vulnerabilities and demonstrate commitment to compliance. Detailed audit reports provided to regulatory authorities reinforce trust and accountability.

Engaging with regulators through consultations, advisory panels, and sandbox initiatives allows institutions to navigate compliance challenges and influence AI-specific regulatory development. These platforms can advocate for frameworks that enable AIPaaS adoption without excessive burdens.

5.3.2 Policy Recommendations

Supportive Regulatory Frameworks

Policymakers are essential in fostering an environment conducive to AIPaaS adoption. While existing regulations safeguard consumer data and financial stability, their rigidity often

impedes innovation. A balanced regulatory framework can encourage AIPaaS adoption while ensuring security and accountability.

Incentive structures, such as tax breaks or grants for organisations investing in AIPaaS, could encourage adoption, particularly among smaller institutions. These incentives would reduce the financial burden associated with upgrading legacy systems or integrating AI technologies (Matsepe & van der Lingen, 2022). Singapore's tax incentives for AI investment offer a model that Johannesburg could replicate, providing a tangible boost to innovation in the financial industry (Singapore Government, 2024).

Establishing regulatory sandboxes for AI technologies allows organisations to test AIPaaS solutions without immediate regulatory constraints. These environments enable experimentation and risk identification, facilitating reliable, compliant implementations.

Encouraging Public-Private Collaboration

Public-private partnerships are crucial to overcoming common challenges in AIPaaS adoption. Collaboration among financial institutions, government bodies, and technology providers can address shared obstacles and co-develop solutions tailored to Johannesburg's needs.

The creation of public-private innovation hubs can help to make this cooperation easier. These hubs might concentrate on creating AI solutions that tackle problems unique to a given industry, such financial inclusion or fraud detection. These hubs can provide scalable and sustainable solutions that benefit the entire ecosystem by combining their resources and skills.

Lessons from international collaborations can inform Johannesburg's approach. For instance, the UK's Financial Conduct Authority partnered with private firms to develop AI-driven compliance tools, demonstrating how public-private partnerships can drive innovation while addressing regulatory concerns (United Kingdom Government, 2024).

5.3.3 Recommendations for Future Research

Emerging Research Areas

Future research should investigate the long-term impacts of AIPaaS adoption on organisational efficiency and BMI. Longitudinal studies can provide a deeper understanding of how AIPaaS influences institutional transformation over time.

The integration of advanced AI technologies, including natural language processing (NLP) and generative AI, within AIPaaS platforms warrants exploration. These capabilities have the potential to enhance customer experience and streamline operations, offering valuable insights for financial institutions (Ernst & Young, 2024d).

Exploring Role-Specific Dynamics

Significant differences in role-specific perceptions of AIPaaS adoption call for further investigation. Studies should examine the unique challenges and opportunities faced by decision-makers, compliance officers, and data specialists. Research on the impact of tailored training programs on adoption rates within specific roles could provide actionable insights for practitioners (Achmat, 2023; Aderibigbe et al., 2023; Ashraf & Atasi, 2022).

Industrial Comparisons

Comparative studies between Johannesburg and other financial hubs, both within Africa and globally, could contextualise the findings of this study. For example, examining AIPaaS adoption in Nairobi or Lagos could highlight regional best practices and common barriers, offering valuable lessons for Johannesburg's financial industry. Such comparisons would also provide a benchmark for evaluating Johannesburg's progress in adopting AI technologies.

5.4 Implications of the Study

Implications for Theory

This study contributes significantly to theoretical frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and business model innovation (BMI) models. In focusing on Johannesburg's financial industry, it extends UTAUT's applicability to emerging markets, highlighting the role of external factors like regulatory frameworks and organisational resistance in shaping technology adoption.

The findings validate UTAUT constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2016)—while identifying nuances

specific to the Johannesburg context, such as heightened concerns about compliance with the Protection of Personal Information Act (POPIA). These insights suggest that UTAUT may require adaptation to account for the legal and infrastructural constraints prevalent in emerging economies.

In terms of BMI models, the study emphasises AIPaaS's transformative role in redefining value creation, delivery, and capture mechanisms. It aligns with existing theories by illustrating how AI enables personalised insurance plans and dynamic lending solutions while incorporating factors like organisational culture and technology readiness. These findings expand BMI frameworks by contextualising them within a developing economy, enhancing our understanding of how AI drives business model evolution in resource-constrained environments.

Additionally, this study addresses a gap in AI adoption literature, which largely focuses on developed markets, by examining the unique challenges and opportunities in Johannesburg. It offers a comprehensive framework for evaluating AI adoption across diverse economic settings, enriching the global discourse on technological innovation in financial services.

Implications for Practice

The study offers actionable insights for financial institutions integrating AIPaaS into their business models. A primary recommendation is aligning AIPaaS adoption with organisational strategy. Institutions should identify specific challenges AIPaaS can address, such as enhancing fraud detection or automating compliance processes, to demonstrate its tangible value and alleviate ROI concerns.

Adopting a phased approach to AIPaaS implementation is critical. Pilot projects allow institutions to evaluate capabilities and address challenges in a controlled setting before full-scale adoption. For example, deploying an AIPaaS-based fraud detection system in one division enables iterative refinement prior to organisation-wide rollout.

Fostering an innovation-driven culture emerged as another key priority. Organisational resistance, often rooted in fears of disruption and job displacement, hinders adoption. Leaders must cultivate adaptability and experimentation through cross-departmental innovation teams, targeted training, and incentives for innovative contributions. Recognising employee-driven

ideas, such as leveraging AIPaaS for personalised customer solutions, can reinforce support for adoption.

Data security and compliance concerns demand robust measures. Institutions should implement advanced encryption and data handling protocols while ensuring transparency with regulators and customers. Demonstrating adherence to POPIA and other standards can build trust and position institutions as responsible technology adopters.

Implications for Policy

Policymakers play a vital role in fostering an ecosystem conducive to innovation. Regulatory frameworks must balance stringent data security with flexibility to promote technological experimentation.

Streamlining regulatory processes can reduce burdens on financial institutions adopting AIPaaS. Regulatory sandboxes, which allow organisations to test AI solutions with temporary compliance exemptions, offer a proven model. Such sandboxes, successfully implemented in regions like the UK, could enable Johannesburg's financial institutions to innovate while managing risk.

Incentives for early adopters, such as tax breaks or grants, can accelerate adoption. Smaller institutions, often constrained by limited resources, would particularly benefit from financial support for integrating AIPaaS. Subsidised training programs could further level the playing field, encouraging industry-wide innovation.

Public-private partnerships can address shared challenges, pooling resources and expertise to develop AI solutions tailored to Johannesburg's unique needs. These collaborations could focus on shared platforms for fraud detection or financial inclusion, benefiting the entire ecosystem while reducing costs.

Finally, policymakers must ensure regulations remain adaptive to evolving AI capabilities. As AIPaaS integrates advanced features like real-time analytics and natural language processing, frameworks must evolve to address emerging risks and opportunities. Continuous dialogue with industry stakeholders is essential to maintain relevant, effective regulatory standards.

5.5 Chapter Summary

This chapter offered a critical examination of the study's findings, connecting them to the theoretical and practical frameworks established in earlier chapters. The results highlighted the significant role of Artificial Intelligence Platform as a Service (AIPaaS) in driving business model innovation (BMI) and enhancing organisational efficiency in Johannesburg's financial industry, thereby reaffirming the study's hypotheses.

Key insights include:

- **Hypothesis 1 (H1):** AIPaaS adoption positively influences BMI. The technology facilitates the development of innovative products, improves customer engagement, and optimises value creation, delivery, and capture processes. These outcomes align Johannesburg's financial institutions with global innovation trends while addressing local challenges such as financial inclusion and resource constraints.
- **Hypothesis 2 (H2):** AIPaaS adoption positively affects organisational efficiency. Improvements were noted in workflow automation, compliance processes, fraud detection, and resource optimisation, underscoring AIPaaS's transformative impact on operational excellence.

The chapter also explored disparities in awareness and perceptions of AIPaaS across professional roles, identifying critical barriers to adoption, including technical challenges, regulatory compliance concerns, and cultural resistance. These barriers were examined alongside enablers such as leadership commitment, innovation culture, and strategic investment in AI infrastructure.

Practical recommendations emphasised enhancing awareness through targeted education and fostering a culture of innovation supported by leadership and cross-departmental collaboration. Data security and compliance strategies were identified as vital for mitigating adoption risks. Policy recommendations included developing balanced regulatory frameworks, providing tax incentives, and promoting public-private partnerships to facilitate innovation and adoption.

The discussion extended to identifying future research opportunities, including longitudinal studies on the sustained impact of AIPaaS, deeper exploration of role-specific adoption dynamics, and comparative analyses with other emerging financial hubs like Nairobi and

Lagos. These areas for further inquiry emphasise the transformative potential of AIPaaS while addressing the complexities of its integration within a regulated, resource-constrained environment.

This chapter synthesised the findings into actionable insights for practitioners, policymakers, and researchers, paving the way for Chapter 6. The final chapter will reflect on the report's overall contributions, limitations, and implications, offering a comprehensive evaluation of the study's relevance to Johannesburg's financial ecosystem and the broader discourse on AI adoption.

Chapter 6: Study Conclusion

6.1 Introduction

This chapter brings the papers' discussion to its conclusion by synthesising its core findings and relating them to the study's objectives, research questions, and hypotheses. It summarises the research, highlights theoretical, practical, and policy implications, and discusses contributions to the academic discourse on Artificial Intelligence Platform as a Service (AIPaaS). The study's practical applications and challenges are critically evaluated, providing a balanced perspective on its outcomes. Furthermore, the chapter addresses limitations of the research and identifies opportunities for future exploration, contributing to the broader understanding of AIPaaS in emerging markets.

The chapter's structure offers a clear and cohesive presentation of the research outcomes. It begins by summarising the study's objectives, hypotheses, and methodological framework before engaging with the findings in detail. This is followed by an analysis of the study's implications, covering theoretical contributions, actionable insights for practitioners, and recommendations for policymakers. The chapter concludes with a critical reflection on the study's limitations and proposed directions for future research. This structure ensures the achieves its goal of providing valuable insights into the adoption of AIPaaS in Johannesburg's financial industry, laying the groundwork for future inquiry and application.

6.2 Summary of the Study

6.2.1 Research Objectives and Hypotheses

The study set out to achieve two key objectives: to explore the role of Artificial Intelligence Platform as a Service (AIPaaS) in driving business model innovation (BMI) and to examine its impact on organisational efficiency within Johannesburg's financial industry. These objectives stemmed from the recognition of AIPaaS's potential to address industry-specific challenges, including regulatory pressures, economic uncertainties, and the need for scalable innovation.
The hypotheses aligned with these goals were:

- **H1:** AIPaaS adoption positively influences business model innovation.
- **H2:** AIPaaS adoption enhances organisational efficiency.

These hypotheses were assessed through a quantitative research framework that provided empirical evidence on how AIPaaS adoption contributes to BMI and operational improvements, offering a nuanced understanding of its transformative potential.

6.2.2 Research Questions Addressed

The research addressed two primary questions:

1. What is the statistical relationship between AIPaaS adoption and business model innovation?
2. What is the impact of AIPaaS on organisational efficiency in Johannesburg's financial industry?

Survey responses from professionals, including decision-makers, compliance officers, and AI/data specialists, illuminated both the opportunities and the barriers to adopting AIPaaS. The findings illustrated how AIPaaS facilitates innovation and efficiency while highlighting role-specific challenges that shape adoption strategies.

6.2.3 Methodological Overview

The study adopted a structured quantitative methodology, utilising surveys distributed via Qualtrics to gather data from banking and insurance professionals. Convenience sampling, complemented by a snowball effect, enabled access to a diverse range of participants, resulting in 82 valid responses.

Data analysis was conducted using SPSS and JASP, employing techniques such as descriptive statistics, reliability analysis, exploratory factor analysis (EFA), and regression and correlation analyses. These rigorous methods ensured that the findings were robust, reliable, and aligned with the study's research objectives, providing both theoretical and practical insights into AIPaaS adoption within the industry.

6.3 Key Findings and Their Implications

6.3.1 Perceptions of AIPaaS Adoption

The study revealed moderate awareness of AIPaaS among participants, with significant variation across roles. AI/Data specialists demonstrated high familiarity due to their technical expertise, while decision-makers recognised its potential for driving business model innovation

(BMI). In contrast, compliance officers exhibited lower awareness, highlighting gaps in knowledge dissemination within organisations. These discrepancies underline the need for role-specific education and training to enhance understanding across all professional levels.

Participants acknowledged AIPaaS's potential to streamline workflows, foster innovation, and enhance customer engagement. However, resistance and scepticism, often rooted in organisational culture and hierarchy, were prevalent. Concerns about job security and increased responsibilities during AIPaaS integration emerged as key barriers, reflecting broader anxieties about technological disruption.

Implication: Role-specific training and inclusive communication strategies are critical. Institutions must develop comprehensive education programs that address these concerns, fostering a unified organisational understanding of AIPaaS adoption.

6.3.2 Impact on Business Model Innovation

AIPaaS demonstrated substantial potential to drive BMI by enabling innovative products and services. Examples include personalised insurance policies based on real-time data and dynamic credit solutions for underserved markets. These applications highlight AIPaaS's role in reshaping value creation, delivery, and capture mechanisms in Johannesburg's financial industry.

Despite these advancements, scalability remains limited. Small-scale implementations and pilot projects dominate, constrained by resource limitations and technical challenges. Institutions in Johannesburg lag behind global counterparts that have integrated AIPaaS into core operations.

Implication: Increased investment in AIPaaS infrastructure and capacity-building initiatives is essential for scaling innovation. Strategic resource allocation will enable institutions to maximise AIPaaS's transformative potential.

6.3.3 Organisational Efficiency

The findings highlighted significant efficiency gains facilitated by AIPaaS in areas such as compliance, fraud detection, and customer service. AI-driven tools automated regulatory

reporting, improved fraud detection accuracy, and streamlined customer interactions, freeing resources for strategic activities and enhancing overall productivity.

However, legacy systems, data integration challenges, and resource constraints limited the full realisation of AIPaaS's potential. Organisational resistance, driven by fears of job loss and increased workloads, further hindered adoption.

Implication: Addressing these barriers requires a multifaceted approach, including upgrading outdated infrastructure, implementing employee training programs, and fostering an organisational culture that embraces adaptability and technological advancement.

6.3.4 Barriers to AIPaaS Adoption

Concerns around data security and regulatory compliance, particularly under South Africa's Protection of Personal Information Act (POPIA), were prominent. Participants highlighted risks associated with handling sensitive customer data and navigating complex compliance frameworks. Financial constraints, particularly for smaller institutions, compounded these challenges.

Implication: Overcoming these barriers necessitates collaboration among institutions, policymakers, and technology providers. Creating a supportive ecosystem with clear regulatory guidelines and shared resources can address security concerns and facilitate widespread AIPaaS adoption.

6.4 Contributions of the Study

6.4.1 Theoretical Contributions

This study advances theoretical frameworks such as business model innovation (BMI) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The findings highlight how regulatory environments and organisational resistance significantly influence technology adoption, especially in markets with stringent compliance and infrastructural constraints. These insights suggest necessary refinements to UTAUT, particularly in contexts where external pressures play a central role.

BMI models are further enriched by incorporating organisational culture and technological readiness as essential factors. Evidence from this study illustrates how AIPaaS transforms value creation, delivery, and capture mechanisms, offering an empirical foundation for refining BMI frameworks in industries with varying degrees of readiness for innovation.

Additionally, this research addresses a notable gap in AI adoption studies by focusing on an emerging economy. While most studies are concentrated on developed markets, the findings provide valuable perspectives on integrating advanced technologies like AIPaaS in resource-constrained environments, contributing to a more global understanding of AI adoption.

6.4.2 Practical Contributions

The study provides actionable strategies for enhancing AIPaaS integration within financial institutions. Creating a culture that embraces innovation emerges as a pivotal enabler, supported by leadership-driven initiatives, cross-functional collaboration, and targeted training programs to address skill gaps and foster adaptability.

Tailored approaches are recommended to address role-specific concerns. For instance, compliance officers prioritise adherence to regulatory frameworks, while decision-makers focus on return on investment and strategic benefits. Addressing these varying priorities ensures sustainable adoption.

Practical solutions for regulatory alignment include robust encryption measures, data anonymisation, and transparent reporting practices. These approaches mitigate risks, strengthen compliance, and build stakeholder confidence in AIPaaS initiatives.

6.4.3 Policy Contributions

The research proposes several policies to encourage widespread AIPaaS adoption. Regulatory sandboxes are identified as effective tools for allowing financial institutions to test AIPaaS solutions within controlled environments. Such initiatives minimise risks associated with large-scale deployments and enable iterative improvement.

Tax incentives and innovation hubs are also highlighted as crucial mechanisms for supporting adoption. Tax reliefs can alleviate resource challenges for smaller institutions, while innovation

hubs foster collaboration between public and private stakeholders to create AI-driven solutions tailored to Johannesburg's financial industry. These recommendations aim to create an equitable and supportive ecosystem for integrating AIPaaS, promoting innovation across the financial industry.

6.5 Limitations of the Study

6.5.1 Methodological Limitations

The study relied on convenience sampling to access participants within Johannesburg's regulated and network-driven financial industry. While practical, this approach reduces the generalisability of findings to other contexts. Self-reported data introduced potential response bias, with participants possibly misrepresenting their familiarity with AIPaaS or its perceived benefits and challenges. Additionally, the exclusion of qualitative interviews limited the depth of insights into organisational dynamics and individual experiences, which could have added valuable context to the findings.

6.5.2 Contextual Limitations

Focusing exclusively on Johannesburg's financial industry, the study's applicability to other emerging markets or industries is restricted. This context-specific focus facilitated a detailed exploration but limits broader generalisations. Banking and insurance firms were prioritised, omitting insights from other financial services such as asset management or fintech startups, which may exhibit distinct adoption dynamics.

6.5.3 Temporal Limitations

The cross-sectional design offered a snapshot of AIPaaS adoption at a single point in time, preventing the study from capturing longitudinal changes. Future research could adopt a longitudinal approach to observe shifts in perceptions, barriers, and outcomes over time, enabling a richer understanding of AIPaaS's evolving influence on the financial industry.

6.6 Recommendations for Future Research

6.6.1 Exploring Long-Term Impacts

Future studies should adopt a longitudinal design to assess how AIPaaS adoption influences organisational efficiency and business model innovation (BMI) over extended periods. Such

research could illuminate the evolving dynamics of adoption and provide a clearer picture of the sustained benefits or challenges associated with integrating AIPaaS. Additionally, investigating emerging features of AIPaaS, such as natural language processing and predictive analytics, could uncover new avenues for its application within the financial industry.

6.6.2 Comparative Analysis Across Industries and Regions

Comparing AIPaaS adoption across financial hubs in other emerging markets, such as Nairobi or Lagos, could identify regional trends and divergences, enriching the contextual understanding of the technology's impact. Expanding research to non-financial industries like healthcare or manufacturing may also highlight broader patterns in AI adoption and reveal transferable best practices.

6.6.3 Investigating Role-Specific Perceptions

The study's findings point to significant variations in how professionals perceive and adopt AIPaaS. Future research could focus on role-specific dynamics, exploring how the expectations and challenges faced by compliance officers, decision-makers, and data specialists shape adoption strategies. Insights from such studies could inform targeted interventions, such as tailored training programs or strategic workshops, to address unique concerns and priorities.

6.6.4 Examining the Role of Regulatory Environments

Given the pivotal role of regulatory compliance in shaping AIPaaS adoption, future research should examine how different regulatory frameworks impact AI adoption in emerging markets. Evaluating policies that balance innovation with compliance could provide actionable insights for creating supportive ecosystems for AIPaaS integration, particularly in highly regulated environments like Johannesburg's financial industry.

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6.7 Final Reflections

6.7.1 Broader Significance of the Study

This research demonstrates the transformative potential of AIPaaS in enhancing innovation and operational efficiency within Johannesburg's financial industry. Addressing challenges such as outdated infrastructure, compliance demands, and organisational resistance has the potential to deliver significant benefits for institutions, customers, and the overall financial ecosystem. The

findings contribute to advancing knowledge on AI adoption in emerging markets, offering insights tailored to contexts often overlooked in global discourse.

6.7.2 Integration with Global Trends

The study aligns Johannesburg's financial industry with global advancements in AI while highlighting distinct dynamics within emerging economies. It contrasts the mature integration seen in developed markets with the nascent yet promising trajectory in Johannesburg. By examining these contexts together, the research emphasizes how emerging markets can play a defining role in advancing AI adoption, particularly by addressing challenges less prominent in advanced economies.

6.7.3 Call to Action

The findings highlight an urgent need for stakeholders to act on the potential of AIPaaS. Financial institutions must commit to developing the infrastructure, skills, and strategies needed for effective adoption. Policymakers should focus on regulatory innovation that balances security with technological progress. Researchers are encouraged to dive deeper into the nuances of AI adoption in resource-constrained environments. These collective efforts are necessary to establish an environment that leverages technology for inclusive and sustainable progress.

References

Achmat, L. (2023). *ETD: Artificial Intelligence Affordances for Organisational Change: Perspectives from South African Artificial Intelligence Practitioners* Cape Town]. OpenUCT. Cape Town. http://hdl.handle.net/11427/39269

Aderibigbe, A. O., Ohenhen, P. E., Nwaobia, N. K., Gidiagba, J. O., & Ani, E. C. (2023). Artificial intelligence in developing countries: bridging the gap between potential and implementation. *Computer Science & IT Research Journal*, *4*(3), 185-199.

Ajigini, O., & Chinamasa, T. (2023). Modelling Digital Transformation Within the Financial Sector: A South African Perspective. *Information Resources Management Journal*, *36*, 1-20. https://doi.org/10.4018/irmj.320642

Ali, O., Abdelbaki, W., Shrestha, A., Elbasi, E., Alryalat, M. A. A., & Dwivedi, Y. K. (2023). A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities. *Journal of Innovation & Knowledge*, *8*(1), 100333. https://doi.org/ARTN 100333
10.1016/j.jik.2023.100333

Amazon Web Services. (2024). How Wipro Improves Financial Fraud Detection with Real-Time Fraud Detection Using IFFD. Retrieved 26 October 2024, from https://aws.amazon.com/blogs/apn/how-wipro-improves-financial-fraud-detection-with-real-time-fraud-detection-using-iffd/

Anica-Popa, I., Anica-Popa, L., Radulescu, C., & Vrîncianu, M. (2021). The Integration of Artificial Intelligence in Retail: Benefits, Challenges and a Dedicated Conceptual Framework. *Amfiteatru Economic*, *23*(56), 120-136. https://doi.org/10.24818/Ea/2021/56/120

Ashraf, A., & Atasi, M. (2022). Business Models, Business Strategies, and Innovations in EdTech Companies: Integration of Learning Analytics and Artificial Intelligence in Higher Education. *Conference Information and Communication Technology*. https://doi.org/10.1109/cict56698.2022.9997887

Bautzer, T., & Nguyen, L. (2023, 07 September 2023). Morgan Stanley to launch AI chatbot to woo wealthy. https://www.reuters.com/technology/morgan-stanley-launch-ai-chatbot-woo-wealthy-2023-09-07/

Bianchi, M., & Brière, M. (2022). Robo-advising: Less AI and more XAI? Augmenting algorithms with humans-in-the-loop. In (pp. 33-58): Cambridge University Press.

Bryman, A. (2016). *Social Research Methods* (5th ed.). Oxford University Press. https://go.exlibris.link/KYwVqcwp

Budree, A., & Gina, B. P. (2023). Factors That Drive the Selection of Business Intelligence Tools in South African Financial Services Providers. *International Journal of Business Intelligence and Data Mining*, *1*(1). https://doi.org/10.1504/ijbidm.2023.10044714

CIO South Africa. (2023). *Beyond Data Integration: Introducing Super iPaaS*. The CIO South Africa. Retrieved May 2024 from https://cio-sa.co.za/articles/beyond-data-integration-introducing-super-ipaas/

Citigroup. (2024). AI in Finance. Retrieved 22 June 2024, from https://www.citigroup.com/global/news/press-release/2024/citi-publishes-new-report-ai-in-finance

Clark, T., Foster, L., Bryman, A., & Sloan, L. (2021). *Bryman's Social Research Methods*. Oxford University Press.

Creswell, J. W., & Creswell, J. D. (2017). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. Sage Publications.

David, L. (2020). The Era of Digital Financial Innovation: Lessons from Economic History on Regulation. *C.D. Howe Institute Commentary*. https://www.semanticscholar.org/paper/af054a963e422c30daffe4af286b7f778647c6f3

Deloitte. (2021). The Financial Services AI Dossier. Retrieved 15 May 2024, from https://www2.deloitte.com/content/dam/Deloitte/us/Documents/deloitte-analytics/us-ai-institute-financial-services-dossier.pdf

Deloitte. (2022). How AI is Shaping the Future of Financial Services. Retrieved 15 November 2023, from https://www.deloitte.com/nz/en/Industries/financial-services/blogs/ai-in-financial-services.html

Deloitte. (no date). *Artificial Intelligence: The next frontier in investment management*. Deloitte. https://www.deloitte.com/content/dam/assets-shared/legacy/docs/perspectives/2022/fsi-artificial-intelligence-investment-mgmt.pdf

Douglas, B. D., Ewell, P. J., & Brauer, M. (2023). Data quality in online human-subjects research: Comparisons between MTurk, Prolific, CloudResearch, Qualtrics, and SONA. *Plos one*, *18*(3), e0279720. https://doi.org/ARTN e0279720
10.1371/journal.pone.0279720

Ernst & Young. (2023). Traditional SA Banking Fraught with Dated Technology, Dated Thinking. Retrieved 14 April 2024, from https://www.ey.com/en_za/industries/financial-services/traditional-sa-banking-fraught-with-dated-technology-dated-thinking

Ernst & Young. (2024a). How Artificial Intelligence is Reshaping the Financial Services Industry. Retrieved August 2024, from https://www.ey.com/en_gr/insights/financial-services/how-artificial-intelligence-is-reshaping-the-financial-services-industry

Ernst & Young. (2024b). How to Navigate Global Trends in Artificial Intelligence Regulation. Retrieved November 2024, from https://www.ey.com/en_za/insights/ai/how-to-navigate-global-trends-in-artificial-intelligence-regulation

Ernst & Young. (2024c). How Your Organization Can Have Confidence in the Opportunities AI Brings. Retrieved November 2024, from https://www.ey.com/en_za/insights/ai/how-your-organization-can-have-confidence-in-the-opportunities-ai-brings

Ernst & Young. (2024d). Unlocking the Future of Banking: The Transformative Power of Generative AI. Retrieved October 2024, from https://www.ey.com/en_ps/industries/financial-services/unlocking-the-future-of-banking-the-transformative-power-of-generative-ai

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (Fifth, North American ed.). Sage Publications Inc.

Forbes Finance, C. (2024). The Impact of AI on the Financial Services Industry. https://www.forbes.com/councils/forbesfinancecouncil/2024/09/13/the-impact-of-ai-on-the-financial-services-industry/

Foss, N. J., & Saebi, T. (2018). Business models and business model innovation: Between wicked and paradigmatic problems. *Long range planning*, *51*(1), 9-21. https://doi.org/10.1016/j.lrp.2017.07.006

França, C. L. (2013). Introductory Approach to Business Model Design for Strategic Sustainable Development. https://www.semanticscholar.org/paper/b97129247588266bdf69d3ff8fa7a9b18cda60a7

Giones, F., & Brem, A. (2017). Digital Technology Entrepreneurship: A Definition and Research Agenda. *Technology Innovation Management Review*, *7*, 44-51.

Gladysz, B., Matteri, D., Ejsmont, K., Corti, D., Bettoni, A., & Guerra, R. H. (2023). Platform-based support for AI uptake by SMEs: guidelines to design service bundles. *Central*

European Management Journal, *31*(4), 463-478. https://doi.org/10.1108/Cemj-08-2022-0096

HSBC Group. (2024). Harnessing the Power of AI to Fight Financial Crime. Retrieved August 2024, from https://www.hsbc.com/news-and-views/views/hsbc-views/harnessing-the-power-of-ai-to-fight-financial-crime

J.P. Morgan Chase. (2023). *AI Boosting Payments Efficiency & Cutting Fraud*. J.P. Morgan Chase&Co. Retrieved February 2024 from https://www.jpmorgan.com/insights/payments/payments-optimization/ai-payments-efficiency-fraud-reduction

Javaid, M., Haleem, A., Singh, R. P., Suman, R., & Khan, S. (2022). A review of Blockchain Technology applications for financial services. *BenchCouncil Transactions on Benchmarks, Standards and Evaluations*, *2*(3), 100073. https://doi.org/10.1016/j.tbench.2022.100073

Karuppiah, K., Sankaranarayanan, B., & Ali, S. M. (2023). A systematic review of sustainable business models: Opportunities, challenges, and future research directions. *Decision Analytics Journal*, *8*, 100272. https://doi.org/10.1016/j.dajour.2023.100272

Kgoale, T. J., & Odeku, K. (2023). An analysis of legal accountability for artificial intelligence systems in the South African financial sector. *De Jure Law Journal*, *56*(1), 191-205. https://doi.org/10.17159/2225-7160/2023/v56a14

Khakhu, S. G. (2023). *Liberating Technologies: automatic speech recognition–AI virtual assistant and the future of language in South Africa* University of Johannesburg (South Africa)].

Lee, J., Suh, T., Roy, D., & Baucus, M. (2019). Emerging Technology and Business Model Innovation: The Case of Artificial Intelligence. *Journal of Open Innovation: Technology, Market, and Complexity*, *5*(3). https://doi.org/10.3390/joitmc5030044

Leech, N., Barrett, K., & Morgan, G. A. (2013). *SPSS for Intermediate Statistics*. Routledge. https://doi.org/10.4324/9781410616739

Li, W., & Ding, H. (2024). Research on the Impact of Technological Innovation on the Financial Services Industry. *Frontiers in Sustainable Development*, *4*(4), 109-119. https://doi.org/10.54691/8qneq173

Liu, L. P., Cui, L. C., Han, Q., & Zhang, C. Y. (2024). The impact of digital capabilities and dynamic capabilities on business model innovation: the moderating effect of organizational inertia. *Humanities & social sciences communications*, *11*(1), 420-410. https://doi.org/ARTN 420
10.1057/s41599-024-02910-z

Manamela, M. M. (2023). *The Role of Artificial Intelligence in Change Management within Organisations in Johannesburg* University of the Witwatersrand]. Johannesburg. https://wiredspace.wits.ac.za/server/api/core/bitstreams/ac05acea-1ec7-40f3-a513-e792ba535402/content

Masenya, T. (2021). Technopreneurship Development: Digital Strategy for Youth Self-Employment in the Digital Economy. *Handbook of Research on Management and Strategies for Digital Enterprise Transformation*. https://doi.org/10.4018/978-1-7998-5015-1.ch010

Matsepe, N. T., & van der Lingen, E. (2022). Determinants of emerging technologies adoption in the South African financial sector. *South African Journal of Business Management*, *53*(1), 2493. https://doi.org/ARTN a2493
10.4102/sajbm.v53i1.2493

McBride, S., & Garcés-Manzanera, A. (2024). Exploring JASP as a data analysis tool in L2 research: a snapshot. *TEISEL. Tecnologías para la investigación en segundas lenguas*, *3*. https://doi.org/10.1344/teisel.v3.45189

Microsoft. (2023). Combat Financial Crime with AI and Advanced Technology from Microsoft. *Industry Solutions*. https://www.microsoft.com/en-us/industry/blog/financial-services/2023/06/05/combat-financial-crime-with-ai-and-advanced-technology-from-microsoft/

Mızrak, F. (2023). Effective Change Management Strategies. In *Perspectives on Artificial Intelligence in Times of Turbulence* (pp. 135-162). IGI Global. https://doi.org/10.4018/978-1-6684-9814-9.ch009

Mossavar Rahmani, F. (2023). The Transformative Impact of AI on Financial Institutions, with a Focus on Banking. *Journal of Engineering and Applied Sciences Technology*, 1-6. https://doi.org/10.47363/jeast/2023(5)192

Motjolopane, I., & Ruhode, E. (2022). Factors driving business model innovation in sample case studies in South Africa. *African Journal of Science Technology Innovation & Development*, *14*(6), 1627-1641. https://doi.org/10.1080/20421338.2021.1977088

Mucha, T., & Seppala, T. (2020). Artificial Intelligence Platforms – A New Research Agenda for Digital Platform Economy. *SSRN Electronic Journal*(76). https://doi.org/10.2139/ssrn.3532937

Mühlroth, C. (2020). Artificial Intelligence as Innovation Accelerator. *SIGMIS-CPR*. https://doi.org/10.1145/3378539.3393869

Mulaudzi, M. B. (2020). *Business model transformation as a response to digital technology adoption amongst manufacturing firms*. University of Johannesburg (South Africa).

Murimbika, M., & Urban, B. (2013). Strategic management practices and corporate entrepreneurship: A cluster analysis of financial and business services firms in South Africa. *African Journal of Business Management*, *7(6)*. https://doi.org/10.5897/ajbm12.1366

Ndou, D. (2004). E-Government for Developing Countries: Opportunities and Challenges. *EJISDC The Electronic Journal on Information Systems in Developing Countries*, *18*, 1-24. https://doi.org/10.1002/j.1681-4835.2004.tb00117.x

Ophoff, J., & Miller, S. (2019). Business Priorities Driving BYOD Adoption: A Case Study of a South African Financial Services Organization. *Issues in Informing Science and Information Technology*, *16*, 165-196. https://doi.org/10.28945/4303

Pallant, J. (2021). *SPSS survival manual: A step by step guide to data analysis using IBM SPSS* (Seventh ed.). Routledge.

Pandey, M. K., & Sergeeva, I. (2022). Artificial Intelligence Impact Evaluation: Transforming Paradigms in Financial Institutions. *World of Economics and Management*, *22*(1), 147-164. https://doi.org/10.25205/2542-0429-2022-22-1-147-164

Price Waterhouse Coopers, S. A. (2024). *South Africa - Major Banks Analysis*. S. A. Price Waterhouse Coopers. https://www.pwc.co.za/en/publications/major-banks-analysis.html#download

Rashid, A. B., & Kausik, M. D. A. K. (2024). AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances*, *7*, 100277. https://doi.org/10.1016/j.hybadv.2024.100277

Ryll, L., Barton, M. E., Zhang, B. Z., McWaters, R. J., Schizas, E., Hao, R., Bear, K., Preziuso, M., Seger, E., Wardrop, R., Rau, P. R., Debata, P., Rowan, P., Adams, N., Gray, M., & Yerolemou, N. (2020). Transforming Paradigms: A Global AI in Financial Services Survey. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3532038

Shahid, N. U., & Sheikh, N. J. (2021). Impact of Big Data on Innovation, Competitive Advantage, Productivity, and Decision Making: Literature Review. *Open Journal of Business and Management*, *09*(02), 586-617. https://doi.org/10.4236/ojbm.2021.92032

Shrestha, N. (2021). Factor Analysis as a Tool for Survey Analysis. *American journal of Applied Mathematics and statistics*, *9*(1), 4-11. https://doi.org/10.12691/ajams-9-1-2

Singapore Government. (2024). *Singapore Budget 2024: Initiatives and Support Measures to Help Businesses Thrive*. Singapore: Singapore Government Retrieved from https://www.edb.gov.sg/en/business-insights/insights/singapore-budget-2024-initiatives-and-support-measures-to-help-businesses-thrive.html#:~:text=Companies%20will%20receive%20a%20Corporate%20Income%20Tax%20%28CIT%29,with%20at%20least%20one%20local%20employee%20in%202023.

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research*, *134*, 574-587. https://doi.org/10.1016/j.jbusres.2021.05.009

Slazus, B. J., & Bick, G. (2022). Factors that Influence FinTech Adoption in South Africa: A Study of Consumer Behaviour towards Branchless Mobile Banking. *Athens Journal of Business & Economics*, *8*(1), 429-450. https://doi.org/10.30958/ajbe.8-1-3

South African Government. (2021). *Protection of Personal Information Act (POPI-Act)*. Johannesburg: South African Government Retrieved from https://www.gov.za/sites/default/files/gcis_document/201409/3706726-11act4of2013protectionofpersonalinforcorrect.pdf

South African Government. (2023). *Gross domestic product, Second quarter 2023*. Pretoria: South African Government Retrieved from https://www.statssa.gov.za/publications/P0441/P04412ndQuarter2023.pdf

Standard Bank South Africa. (2024). The Role of AI in Detecting, Monitoring, and Preventing Payments Fraud. Retrieved 14 November 2024, from https://www.standardbank.co.za/southafrica/news-and-media/newsroom/the-role-of-ai-in-detecting-monitoring-and-preventing-payments-fraud

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *Int J Med Educ*, *2*, 53-55. https://doi.org/10.5116/ijme.4dfb.8dfd

United Kingdom Government. (2024). *A Pro-Innovation Approach to AI Regulation: Government Response*. U. K. Government. https://www.gov.uk/government/consultations/ai-regulation-a-pro-innovation-approach-policy-proposals/outcome/a-pro-innovation-approach-to-ai-regulation-government-response

University of Johannesburg Business School. (2022). *Emerging Technologies in South Africa: A Landscape Analysis*. U. o. J. B. School. https://www.uj.ac.za/wp-content/uploads/2022/02/uj-emtech-digital.pdf

Urban, B. (2017). Corporate Entrepreneurship in South Africa: The Role of Organizational Factors and Entrepreneurial Alertness in Advancing Innovativeness. *Journal of Developmental Entrepreneurship*, *22*(03). https://doi.org/10.1142/s1084946717500157

Urban, B., & Maphumulo, M. (2022). The moderating effects of entrepreneurial orientation on technological opportunism and innovation performance. *European journal of innovation management*, *25*(3), 901-921. https://doi.org/10.1108/Ejim-12-2020-0509

Urban, B., & Verachia, A. (2019). Organisational antecedents of innovative firms: a focus on entrepreneurial orientation in South Africa. *International Journal of Business Innovation and Research*, *18*(1), 128-144. https://doi.org/10.1504/ijbir.2019.096905

Vallentyn, G. (2021). *Exploring How Traditional Banks In SA Can Improve Their Competitiveness Through Investment In Big Data Technology* Nelson Mandela]. Eastern Cape.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead. *Journal of the association for Information Systems*, *17*(5), 328-376. https://doi.org/DOI 10.17705/1jais.00428

Yaiprasert, C., & Hidayanto, A. N. (2024). AI-powered ensemble machine learning to optimize cost strategies in logistics business. *International Journal of Information Management Data Insights*, *4*(1), 100209. https://doi.org/10.1016/j.jjimei.2023.100209

Appendices

Participant Information Sheet with Consent Clause

Title: AI-driven Business Model Innovation: The Impact of AI Integration Platform as a Service (AIPaaS) on Johannesburg, South Africa's Financial Service Industry.

Researcher: Israel Notwane-Skosana
Affiliation: University of the Witwatersrand, Johannesburg, Business School.
Ethics Protocol Number: WBS/EN681632/174

Dear Participant,

My name is Israel Notwane-Skosana. I am a master's student in Master of Management in Entrepreneurship and New Venture Creation at the University of the Witwatersrand, Johannesburg. My supervisor is Professor Boris Urban. I am conducting a research study about the Impact of AI Integration Platform as a Service (AIPaaS) on Johannesburg, South Africa's Financial Service Industry. The study title is AI-driven Business Model Innovation: The Impact of AI Integration Platform as a Service (AIPaaS) on Johannesburg, South Africa's Financial Service Industry.

I am inviting you to take part in answering a questionnaire. If you decide to take part, your participation in this research study will last about 20-30 minutes. The research activity will take place at your convenience through an online platform.

With your permission, I would like to electronically record your answers. This data will be stored in password-protected computers after they are downloaded from the online platform and deleted after three (3) years. Only the researcher will have access to the data and my supervisor on request.

During the research activity, I will need to ask for some personal information about you, including gender, age, and level of education.

The answering of the questionnaire will be confidential and anonymous. When I share the results of the research study, I will not include your name or anything else that could identify you. With your permission, other researchers may use the data collected from this research study, but your name and any personal information will not be used or passed on.

If you decide to take part in the research study, it should be because you want to volunteer. You do not have to take part. You can stop being in the study at any time. You do not have to answer any questions if you do not want to. You will not get any direct benefits if you choose to join the research study. You will not lose any services, benefits, or rights you would normally have if you decide not to join. Taking part in the research study will not cost you anything. You will not be paid for being in this research study.

The risks for this research study are no more than what happens in everyday life in your line of work OR some of the questions asked may be company sensitive. If this is the case, please do not proceed with the survey or skip the questions.

This research study will be written as a research report. The report will be available on the university library website. If you would like to receive a summary of this report, I will be happy to send it to you.

If you have any questions during or afterwards about this research study, feel free to contact me or my supervisor Professor Boris Urban on the details listed below. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za.

Consent.

By continuing with this study through answering the survey, you acknowledge that you have read as well as understood this information and that you consent and confirm that your participation is voluntary, and you may withdraw at any time.

Yours sincerely,

Researcher:

Israel Notwane-Skosana,

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0723799148

Supervisor:

Professor Boris Urban,

Boris.urban@wits.ac.za

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Research Survey Questionnaire

Start of Block: Participant Information

Q2 What is your current role within your organisation?

- ○ Decision-Maker/Executive (1)
- ○ Legal Expert/Compliance Officer (2)
- ○ AI/Data Specialist (3)

Q3 How many years of experience do you have in the financial services industry?

- ○ 0-2 years (1)
- ○ 3-5 years (2)
- ○ 6-9 years (3)
- ○ 10-14 years (4)
- ○ 15-19 years (5)
- ○ 20 or more years (6)

Q4 What is your primary affiliation within the financial industry?

- ○ Banking Services (1)
- ○ Wealth Management Services (2)

○ Insurance Services (3)

○ Investment Funds Services (4)

○ Credit Unions Services (5)

○ Mutual Funds (6)

○ Other (please specify) (7) _____

End of Block: Participant Information

Start of Block: Perception of AIPaaS

Q5 **Familiarity with AIPaaS:**

Please rate your level of familiarity with AI Integration Platform as a Service (AIPaaS).

○ Extremely Familiar (1)

○ Largely Familiar (2)

○ Moderately familiar (3)

○ Neutral (4)

○ Moderately Unfamiliar (5)

○ Largely Unfamiliar (6)

○ Completely Unfamiliar (7)

Q6 **Perception of AIPaaS Usefulness:**

To what extent do you believe AIPaaS can enhance business operations?

- ○ Strongly agree (1)
- ○ Agree (2)
- ○ Somewhat agree (3)
- ○ Neutral (4)
- ○ Somewhat disagree (5)
- ○ Disagree (6)
- ○ Strongly disagree (7)

Q7 **Perception of AIPaaS Effectiveness:**

How effective do you perceive AIPaaS to be in improving business performance?

- ○ Extremely effective (1)
- ○ Very effective (2)
- ○ Moderately effective (3)
- ○ Neutral (4)
- ○ Slightly Effective (5)
- ○ Ineffective (6)
- ○ Extremely Ineffective (7)

Q8 **Attitudes Towards Integrating AIPaaS:**

Please indicate your attitude towards integrating AIPaaS into existing business models.

- ○ Strongly Support Integration (1)
- ○ Support Integration (2)
- ○ Somewhat Support Integration (3)
- ○ Neutral (4)
- ○ Somewhat Oppose Integration (5)
- ○ Oppose Integration (6)
- ○ Strongly Oppose Integration (7)

Q9 **Perceived Impact of AIPaaS on Business Models:**

How do you anticipate the integration of AIPaaS will impact existing business models?

- ○ Extremely Positively (1)
- ○ Positively (2)
- ○ Somewhat Positively (3)
- ○ Neutral (4)
- ○ Somewhat Negatively (5)
- ○ Negatively (6)
- ○ Extremely Negatively (7)

End of Block: Perception of AIPaaS

Start of Block: Impact on Business Model Innovation

Q10 **Impact on Product/Service Offerings:**

Please rate the extent to which you believe AIPaaS positively influences the innovation of product/service offerings within your organisation.

- ○ Extremely Positive Impact (1)
- ○ Positive Impact (2)
- ○ Substantial Positive Impact (3)
- ○ Neutral (4)
- ○ Unsubstantial Positive Impact (5)
- ○ Minimal Positive Impact (6)
- ○ No Positive Impact (7)

Q11 **Impact on Customer Experience:**

How do you perceive the influence of AIPaaS on enhancing customer experience within your organisation?

- ○ Exceptional Influence (1)
- ○ Significant Influence (2)
- ○ Considerable Influence (3)
- ○ Neutral (4)
- ○ Some Influence (5)

○ Very Little Influence (6)

○ No Influence at All (7)

Q12 **Impact on Operational Efficiency:**

To what extent does the integration of AIPaaS improve operational efficiency within your organisation?

○ Completely (1)

○ Significantly (2)

○ Considerable (3)

○ Neutral (4)

○ Somewhat (5)

○ Very Minimally (6)

○ Not at All (7)

Q13 **Contribution to Organisational Innovation:**

Please rate the extent to which you perceive AIPaaS as a driver of innovation within your organisation.

○ Primary Driver of Innovation (1)

○ Major Driver of Innovation (2)

○ Moderate Driver of Innovation (3)

○ Neutral (4)

○ Some Driver of Innovation (5)

○ Minor Driver of Innovation (6)

○ Not a Driver of Innovation (7)

End of Block: Impact on Business Model Innovation

Start of Block: Innovation Dynamics

Q14 **Influence on Innovation Dynamics:**

Please rate the extent to which AIPaaS positively influences innovation dynamics within your organisation's operations.

○ Significantly Enhances Innovation Dynamics (1)

○ Moderately Enhances Innovation Dynamics (2)

○ Somewhat Enhances Innovation Dynamics (3)

○ Neutral Influence on Innovation Dynamics (4)

○ Moderately Inhibits Innovation Dynamics (5)

○ Significantly Inhibits Innovation Dynamics (6)

○ Severely Inhibits Innovation Dynamics (7)

Q15 **Organisation's Adaptability to Technological Changes:**

How well do you believe your organisation adapts to technological changes such as the integration of AIPaaS?

- ○ Highly Adaptable to Technological Changes (1)
- ○ Moderately Adaptable to Technological Changes (2)
- ○ Somewhat Adapts to Technological Changes (3)
- ○ Neutral (4)
- ○ Struggles to Adapt to Technological Changes (5)
- ○ Has Limited Adaptability to Technological Changes (6)
- ○ Resistant to Technological Changes (7)

Q16 **Perception of Embracing Innovation:**

To what extent does your organisation embrace innovation including the adoption of AIPaaS?

- ○ Fully Embraces Innovation (1)
- ○ Largely Embraces Innovation (2)
- ○ Somewhat Embraces Innovation (3)
- ○ Neutral (4)
- ○ Hesitates to Embrace Innovation (5)
- ○ Reluctant to Embrace Innovation (6)
- ○ Resists Innovation Initiatives (7)

Q17 **Degree of Innovation Culture:**

How strong is the culture of innovation within your organisation particularly regarding the integration of new technologies like AIPaaS?

- ○ Has a Robust Culture of Innovation (1)
- ○ Has a Moderately Strong Culture of Innovation (2)
- ○ Has Some Elements of an Innovation Culture (3)
- ○ Neutral (4)
- ○ Lacks a Significant Innovation Culture (5)
- ○ Has a Weak Innovation Culture (6)
- ○ Has No Discernible Innovation Culture (7)

Q18 **Openness to Experimentation:**

Rate the degree to which your organisation encourages experimentation and risk-taking in the context of adopting new technologies such as AIPaaS.

- ○ Strongly Encourages Experimentation (1)
- ○ Moderately Encourages Experimentation (2)
- ○ Somewhat Encourages Experimentation (3)
- ○ Neutral (4)
- ○ Hesitant Towards Experimentation (5)
- ○ Discourages Experimentation (6)
- ○ Strongly Discourages Experimentation (7)

End of Block: Innovation Dynamics

Start of Block: Business Model Innovation Barriers

Q19 **Perceived Barriers to Integration:**

Please rate the extent to which you believe potential barriers and challenges hinder the successful integration of AIPaaS within your organisation.

- ○ Very Few Barriers and Challenges Exist (1)
- ○ Minor Barriers and Challenges (2)
- ○ Some Barriers and Challenges (3)
- ○ Moderate Barriers and Challenges (4)
- ○ Significant Barriers and Challenges (5)
- ○ Major Barriers and Challenges (6)
- ○ Numerous Significant Barriers and Challenges (7)

Q20 **Concerns about Data Security:**

How concerned are you about the data security implications associated with integrating AIPaaS into your organisation's infrastructure?

- ○ Not Concerned at All (1)
- ○ Slightly Concerned (2)
- ○ Somewhat Concerned (3)
- ○ Moderately Concerned (4)

- ○ Concerned (5)
- ○ Very Concerned (6)
- ○ Extremely Concerned (7)

Q21 **Privacy Issues:**

To what extent do you anticipate privacy issues arising from the integration of AIPaaS within your organisation?

- ○ No Anticipated Privacy Issues (1)
- ○ Few Anticipated Privacy Issues (2)
- ○ Some Anticipated Privacy Issues (3)
- ○ Moderate Number of Anticipated Privacy Issues (4)
- ○ Significant Anticipated Privacy Issues (5)
- ○ Many Anticipated Privacy Issues (6)
- ○ Numerous Significant Anticipated Privacy Issues (7)

Q22 **Regulatory Compliance Concerns:**

How concerned are you about ensuring regulatory compliance when integrating AIPaaS into your organisation's operations?

- ○ Not Concerned at All (1)
- ○ Slightly Concerned (2)

○ Somewhat Concerned (3)

○ Moderately Concerned (4)

○ Concerned (5)

○ Very Concerned (6)

○ Extremely Concerned (7)

Q23 **Organisational Resistance to Change:**

Rate the level of organisational resistance to change that you anticipate when implementing AIPaaS.

○ No Resistance to Change Expected (1)

○ Low Level of Resistance to Change Expected (2)

○ Some Resistance to Change Expected (3)

○ Moderate Level of Resistance to Change Expected (4)

○ Significant Resistance to Change Expected (5)

○ High Level of Resistance to Change Expected (6)

○ Very High Level of Resistance to Change Expected (7)

End of Block: Business Model Innovation Barriers

Start of Block: Future Outlook

Q24 **Expectations for AI-driven Innovation:**

To what extent do you believe that AI-driven business model innovation will positively shape the future of the financial services industry?

- ○ Extremely Optimistic about Its Positive Impact (1)
- ○ Very Optimistic (2)
- ○ Optimistic (3)
- ○ Neutral (4)
- ○ Sceptical (5)
- ○ Very Sceptical (6)
- ○ Extremely Sceptical about Its Negative Impact (7)

Q25 **Long-term Impact of AIPaaS:**

How confident are you in the ability of AIPaaS to contribute to significant and sustainable innovation within the financial services industry in the long term?

- ○ Highly Confident in Its Positive Long-term Impact (1)
- ○ Confident (2)
- ○ Moderately Confident (3)
- ○ Neutral (4)
- ○ Not Very Confident (5)
- ○ Uncertain (6)
- ○ Highly Sceptical about Its Long-term Effectiveness (7)

Q26 **Industry Transformation Expectations:**

To what degree do you anticipate that AIPaaS will lead to a fundamental transformation of business models and operations within the financial services industry?

- ○ Anticipate Significant Positive Transformation (1)
- ○ Expect Moderate Positive Transformation (2)
- ○ Expect Some Level of Positive Transformation (3)
- ○ Neutral (4)
- ○ Expect Minimal Positive Transformation (5)
- ○ Expect Limited or Negative Transformation (6)
- ○ Anticipate Significant Negative Transformation or Disruption (7)

End of Block: Future Outlook

Start of Block: Additional Comments

Q27 Comments to Share?

_____

_____

_____

_____

_____

End of Block: Additional Comments

Start of Block: Demographics

Q28 Gender:

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary (3)
- ○ Prefer not to say (4)
- ○ Other (please specify) (5) _____

Q29 Age:

- ○ 18-24 (1)
- ○ 25-34 (2)
- ○ 35-44 (3)
- ○ 45-54 (4)
- ○ 55-64 (5)
- ○ 65 and older (6)

Q30 Highest Level of Education:

- ○ Matric (1)
- ○ Post-matric Diploma (2)

- ○ Bachelor's (3)
- ○ Honours/Postgraduate Diploma/BTech (4)
- ○ Master's (5)
- ○ Doctorate (6)
- ○ Other (please specify) (7) _____

End of Block: Demographics

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/EN681632/174

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

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

Project title	AI-driven business model innovation: The impact of AI integration platform as a service (AiPaaS) in the financial service industry in Johannesburg, South Africa
Investigator / Researcher	Mx Israel Notwane-Skosana
Nature of Project	MM in Entrepr & New Venture Creation
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	10/07/2024
Expiry date	Date of submission of the project / research report
Chairperson	Dr Ayanda Magida ☎ +27 11 717 3953 ✉ ayanda.magida@wits.ac.za

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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

10 July 2024
Date:

Additional Data Results

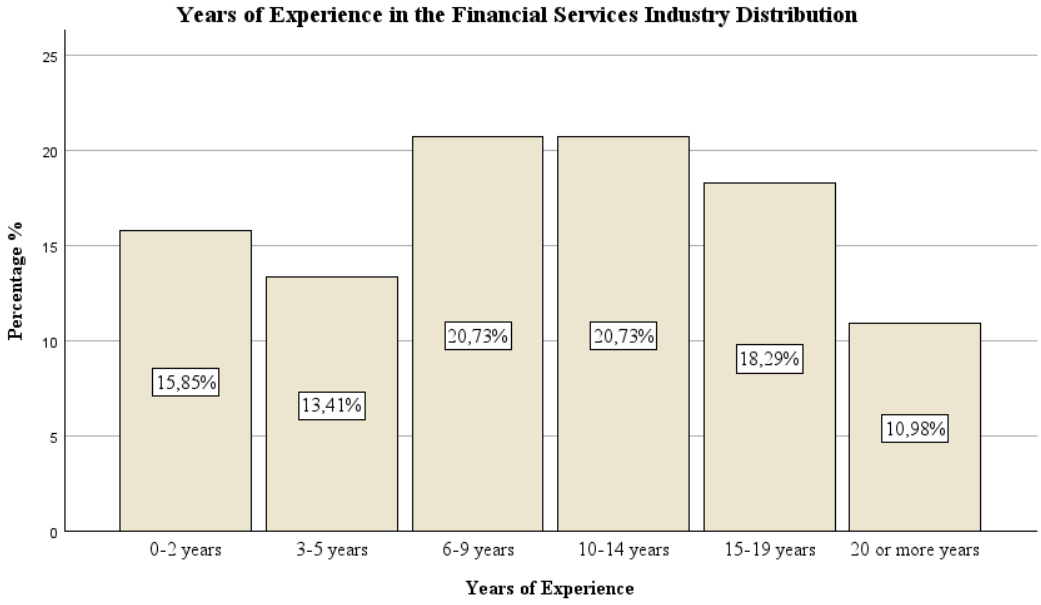
a. Supplementary Participant Demographics

Frequency Table: Age Distribution Across Professional Roles

Frequency Distribution of Age Groups Across Professional Roles

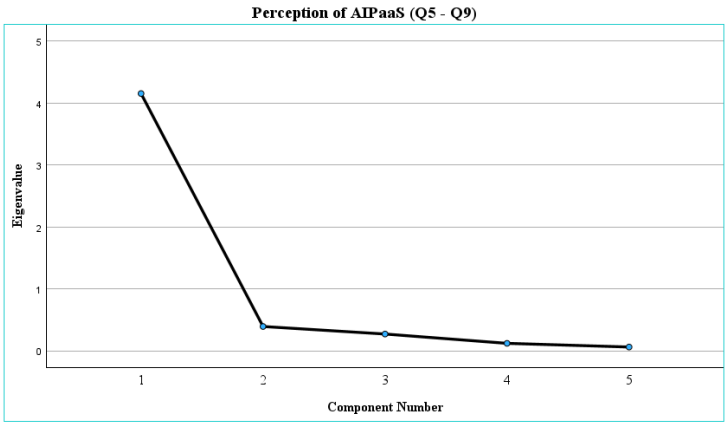
		Q29											
		18-24		25-34		35-44		45-54		55-64		Total	
		N	%	N	%	N	%	N	%	N	%	N	%
Q2	Decision-Maker/Executive	1	50,0%	1	4,5%	7	22,6%	10	52,6%	8	100,0%	27	32,9%
	Legal Expert/Compliance Officer	0	0,0%	0	0,0%	20	64,5%	7	36,8%	0	0,0%	27	32,9%
	AI/Data Specialist	1	50,0%	21	95,5%	4	12,9%	2	10,5%	0	0,0%	28	34,1%
Total		2	100,0%	22	100,0%	31	100,0%	19	100,0%	8	100,0%	82	100,0%

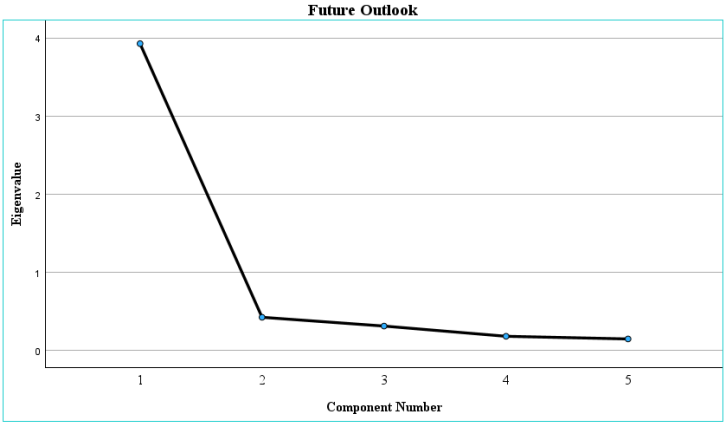
Bar Graph: Distribution of Years of Experience within the Financial Industry

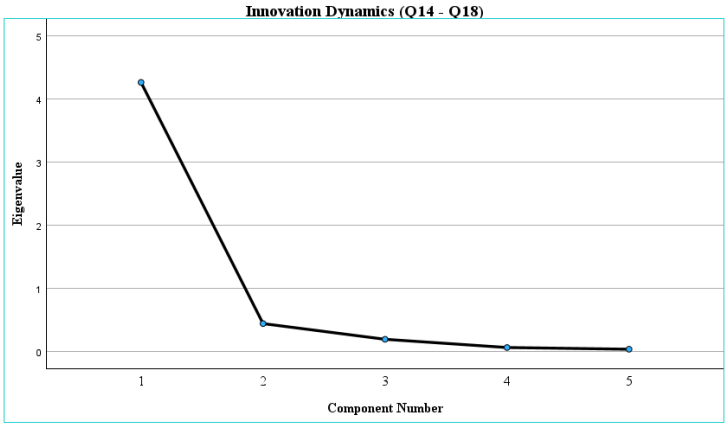


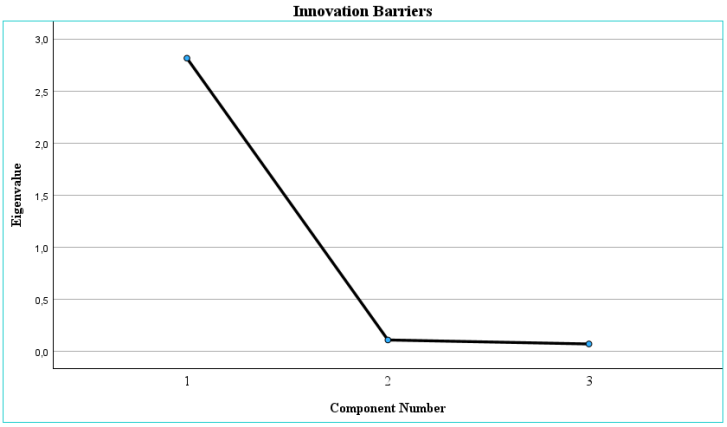
b. Exploratory Factor Analysis (EFA)

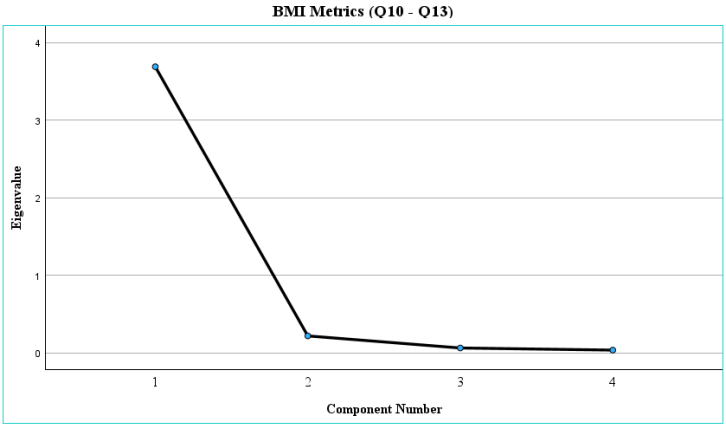
Eigenvalue Scree Plot (Constructs)











Rotated Component Matrix (Synthesised Pattern Matrix)

Pattern Matrix[a]

	Component 1	Component 2
Q12	1,038	-,118
Q13	1,019	
Q10	1,008	-,185
Q11	,998	
Q25	,983	
Q26	,924	
Q16	,901	
Q17	,860	
Q6	,843	,153
Q9	,841	,110
Q24	,837	,150
Q7	,796	
Q14	,785	
Q19	,778	,192
Q8	,724	,265
Q18	,712	,230
Q15	,557	,391
Q20	-,193	1,062
Q21		,920
Q22		,897
Q23		,811
Q5	,406	,486

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.[a]

a. Rotation converged in 3 iterations.

c. Descriptive Testing and Construct Analysis (Table)

Section	Items	Definition	Hypothesis Alignment	Key Findings	Sources
1. AIPaaS Perception (Q5–Q9)	Q5: Familiarity, Q6: Usefulness, Q7: Effectiveness, Q8: Attitude, Q9: Impact on Models	Examines the awareness, perceived usefulness, and attitudes toward integrating AIPaaS.	Positive perceptions of AIPaaS predict willingness for adoption and integration.	Respondents recognise AIPaaS benefits but cite varying familiarity levels.	Venkatesh et al. (2016); Urban (2017); Deloitte (2022); Foss & Saebi (2018)
2. AIPaaS BMI Impact Metrics (Q10–Q13)	Q10: Product Impact, Q11: Customer Experience, Q12: Efficiency, Q13: Organisational Innovation	Evaluates how AIPaaS contributes to innovation in products/services and operational efficiency.	AIPaaS adoption positively influences innovation in business models and processes.	AIPaaS demonstrates strong contributions to product and operational innovations.	Foss & Saebi (2017); Deloitte (2024); Ernst & Young (2024); CIO South Africa (2023)
3. AIPaaS Innovation Dynamics (Q14–Q18)	Q14: Influence, Q15: Adaptability, Q16: Embracing Innovation, Q17: Innovation Culture, Q18: Experimentation	Assesses organisational adaptability, culture, and experimentation as enablers for AIPaaS adoption.	Innovation culture and adaptability strongly impact the success of AIPaaS integration.	Organisations with strong innovation dynamics show higher AIPaaS adoption readiness.	Urban & Maphumulo (2021); Giones & Brem (2017); Murimbika & Urban (2013); Achmat (2023)
4. AIPaaS Barriers (Q19–Q23)	Q19: Barriers, Q20: Data Security, Q21: Privacy, Q22: Compliance, Q23: Resistance to Change	Identifies challenges, including security, compliance, and resistance to adopting AIPaaS.	Barriers to AIPaaS adoption hinder business model innovation and operational improvement.	Data security and compliance concerns are critical barriers to adoption.	Kgoale & Odeku (2023); Deloitte (2021); Mulaudzi (2020); Standard Bank Report (2024)
5. AIPaaS Future Outlook (Q24–Q26)	Q24: Expectations, Q25: Long-Term Impact, Q26: Industry Transformation	Explores anticipated long-term impacts and transformative potential of AIPaaS adoption.	AIPaaS drives long-term transformation and future competitiveness in financial industries.	Positive future expectations for AIPaaS align with its potential to revolutionise industries.	Javaid et al. (2022); Foss & Saebi (2017); Ernst & Young (2024); Deloitte (2024)

d. Reliability and Validity (Synthesised Insights)

Item-Total Statistics Table

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q5	55,38	591,003	,780	.	,983
Q6	56,18	594,843	,947	.	,982
Q7	55,90	589,842	,784	.	,983
Q8	55,99	586,506	,920	.	,982
Q9	55,95	588,714	,908	.	,982
Q10	55,85	582,966	,817	.	,983
Q11	55,83	577,625	,927	.	,982
Q12	55,80	574,628	,908	.	,982
Q13	55,80	578,307	,916	.	,982
Q14	56,04	594,900	,800	.	,983
Q15	56,12	593,763	,855	.	,983
Q16	55,94	582,255	,926	.	,982
Q17	55,95	584,294	,893	.	,982
Q18	56,09	586,449	,876	.	,982
Q19	55,27	585,137	,914	.	,982
Q20	54,22	593,482	,669	.	,984
Q21	55,02	593,827	,731	.	,983
Q22	54,13	577,155	,765	.	,984
Q23	55,05	595,207	,711	.	,984
Q24	55,71	582,234	,941	.	,982
Q25	55,80	570,949	,930	.	,982
Q26	55,60	572,318	,887	.	,982

Cronbach's Alpha if Item Deleted Table

Reliability Statistics

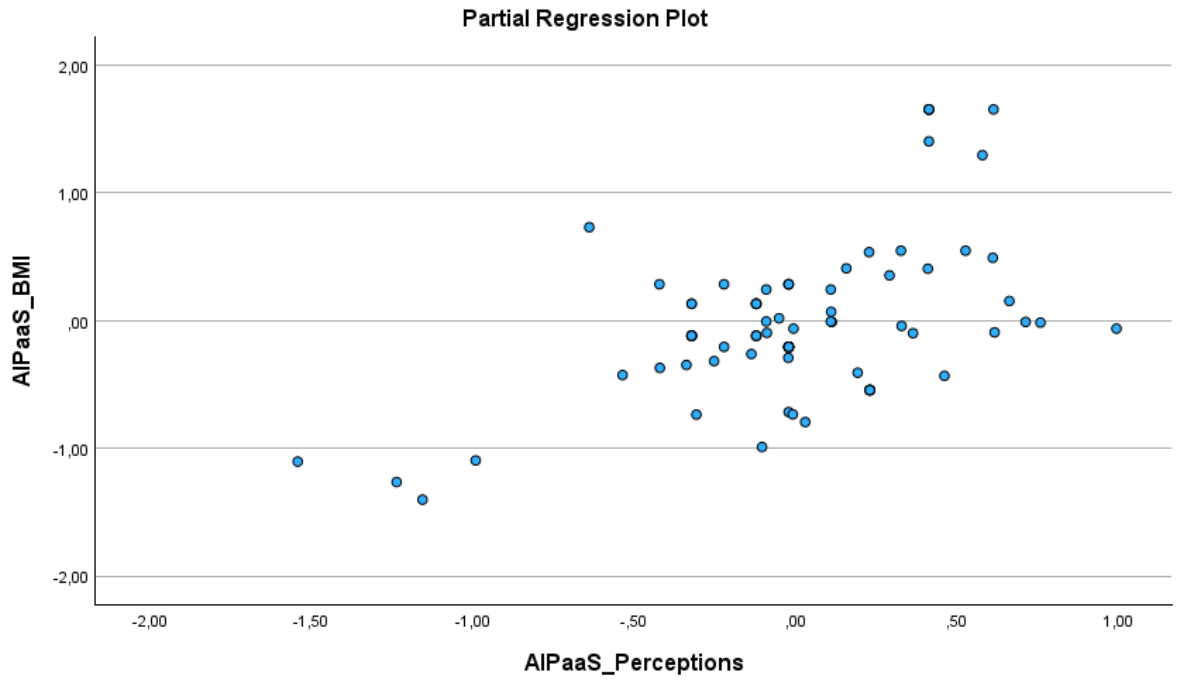
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,983	,984	22

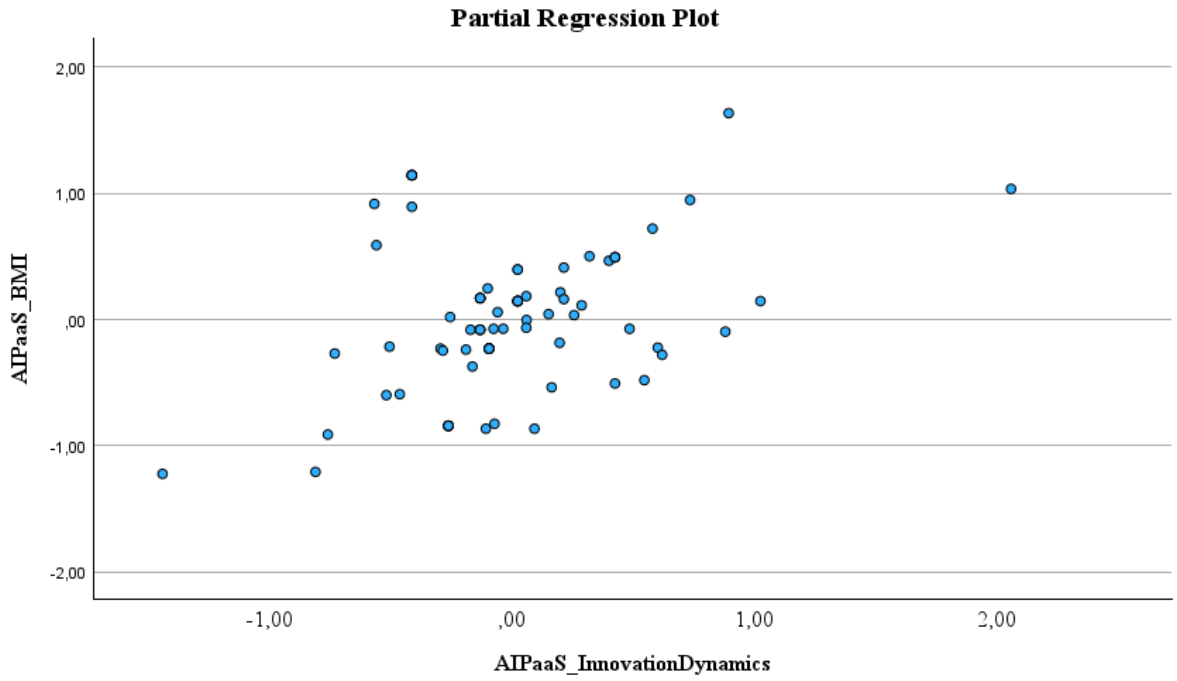
Inter-Item Correlation Matrix

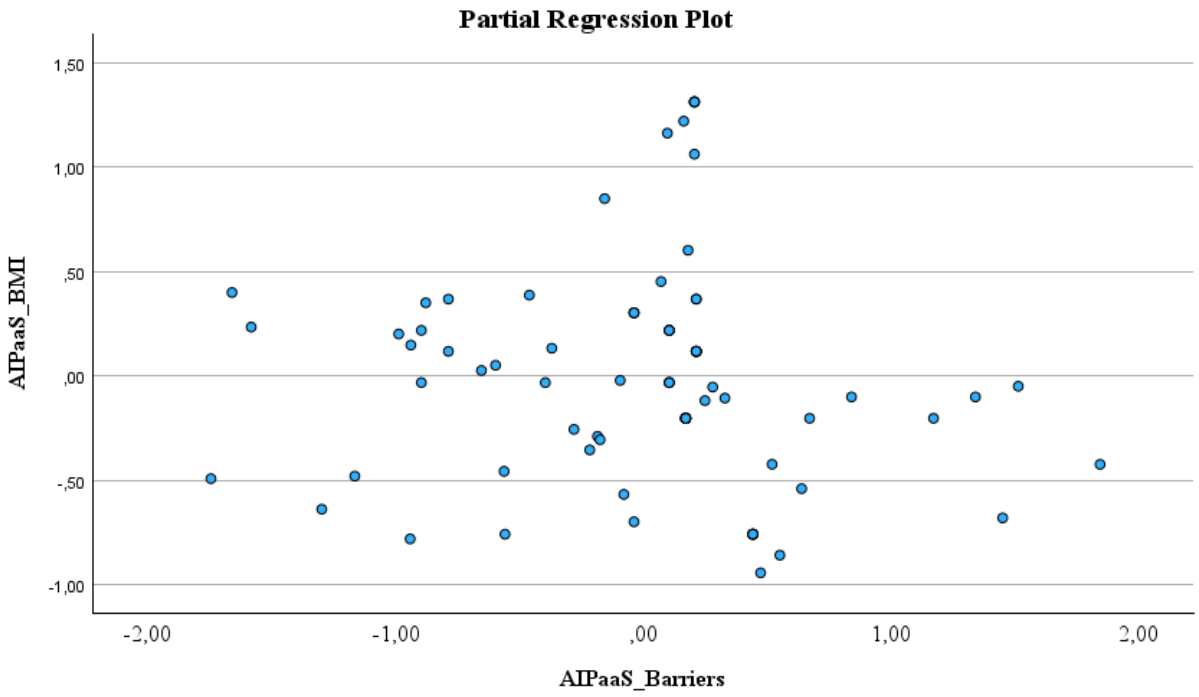
Inter-Item Correlation Matrix

	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22	Q23	Q24	Q25	Q26
Q5	1,000	,820	,616	,815	,688	,600	,695	,703	,703	,629	,757	,676	,617	,628	,741	,626	,668	,686	,603	,731	,681	,646
Q6	,820	1,000	,802	,932	,842	,810	,895	,886	,884	,757	,860	,886	,840	,847	,864	,607	,641	,707	,626	,912	,923	,857
Q7	,616	,802	1,000	,755	,721	,699	,735	,759	,737	,609	,713	,759	,741	,749	,668	,484	,501	,567	,516	,756	,790	,704
Q8	,815	,932	,755	1,000	,866	,769	,846	,857	,842	,731	,896	,869	,802	,811	,835	,623	,678	,715	,645	,840	,856	,779
Q9	,688	,842	,721	,866	1,000	,812	,899	,880	,924	,773	,732	,839	,818	,748	,843	,560	,668	,690	,643	,876	,879	,802
Q10	,600	,810	,699	,769	,812	1,000	,853	,806	,866	,661	,672	,786	,743	,709	,791	,436	,479	,486	,526	,805	,858	,788
Q11	,695	,895	,735	,846	,899	,853	1,000	,949	,962	,806	,737	,873	,850	,769	,892	,505	,633	,620	,614	,905	,913	,894
Q12	,703	,886	,759	,857	,880	,806	,949	1,000	,931	,801	,747	,890	,862	,790	,856	,460	,551	,599	,579	,879	,899	,867
Q13	,703	,884	,737	,842	,924	,866	,962	,931	1,000	,810	,719	,855	,825	,752	,885	,498	,609	,592	,584	,896	,919	,869
Q14	,629	,757	,609	,731	,773	,661	,806	,801	,810	1,000	,632	,740	,710	,646	,771	,483	,588	,580	,561	,747	,769	,804
Q15	,757	,860	,713	,896	,732	,672	,737	,747	,719	,632	1,000	,857	,825	,874	,767	,629	,693	,694	,614	,759	,766	,702
Q16	,676	,886	,759	,869	,839	,786	,873	,890	,855	,740	,857	1,000	,952	,924	,855	,540	,611	,681	,610	,886	,911	,843
Q17	,617	,840	,741	,802	,818	,743	,850	,862	,825	,710	,825	,952	1,000	,942	,826	,548	,613	,666	,569	,847	,854	,818
Q18	,628	,847	,749	,811	,748	,709	,769	,790	,752	,646	,874	,924	,942	1,000	,788	,632	,631	,682	,591	,827	,847	,789
Q19	,741	,864	,668	,835	,843	,791	,892	,856	,885	,771	,767	,855	,826	,788	1,000	,633	,692	,700	,603	,899	,848	,859
Q20	,626	,607	,484	,623	,560	,436	,505	,460	,498	,483	,629	,540	,548	,632	,633	1,000	,834	,812	,738	,603	,530	,535
Q21	,668	,641	,501	,678	,668	,479	,633	,551	,609	,588	,693	,611	,613	,631	,692	,834	1,000	,785	,707	,659	,589	,568
Q22	,686	,707	,567	,715	,690	,486	,620	,599	,592	,580	,694	,681	,666	,682	,700	,812	,785	1,000	,790	,751	,637	,625
Q23	,603	,626	,516	,645	,643	,526	,614	,579	,584	,561	,614	,610	,569	,591	,603	,738	,707	,790	1,000	,648	,628	,609
Q24	,731	,912	,756	,840	,876	,805	,905	,879	,896	,747	,759	,886	,847	,827	,899	,603	,659	,751	,648	1,000	,926	,900
Q25	,681	,923	,790	,856	,879	,858	,913	,899	,919	,769	,766	,911	,854	,847	,848	,530	,589	,637	,628	,926	1,000	,895
Q26	,646	,857	,704	,779	,802	,788	,894	,867	,869	,804	,702	,843	,818	,789	,859	,535	,568	,625	,609	,900	,895	1,000

e. Supplementary Regression Analyses (Partial Plots)







f. Thematic Analysis (for Depth – Synthesised)

Barriers to Adoption Themes

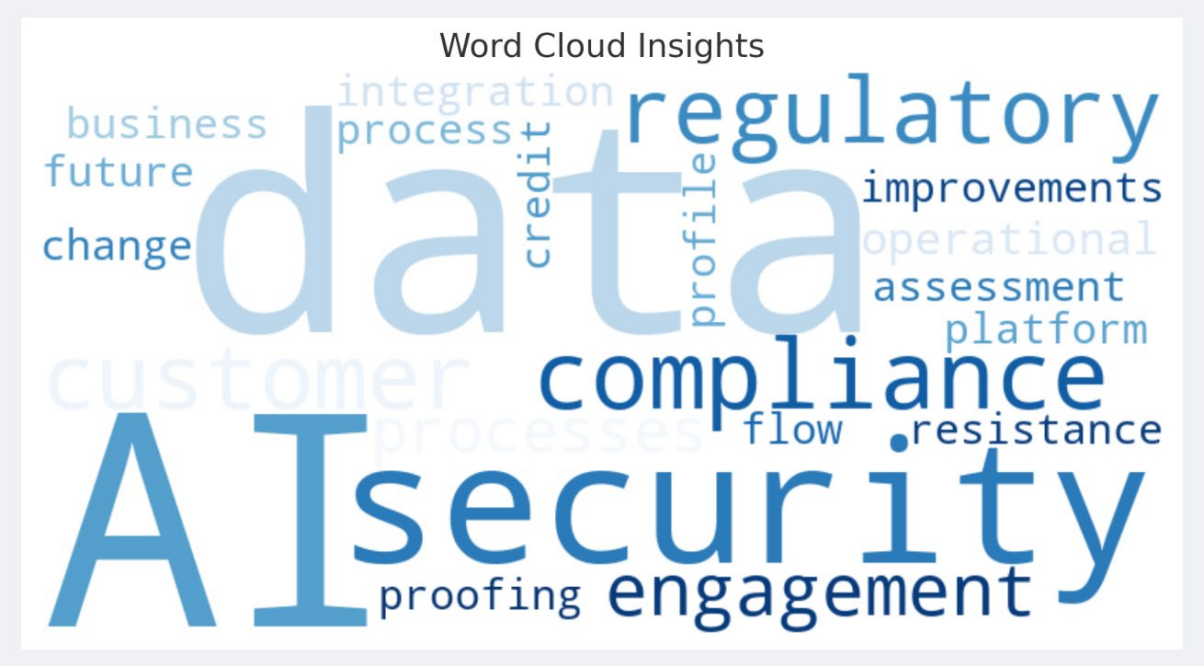
Theme	Frequency
Data Security Concerns	**High**
Regulatory and Compliance Issues	**High**
Legacy Systems and Frameworks	**Moderate**
Lack of Convincing Evidence of Impact	**Moderate**
Resistance to Change	**Low**

Opportunities Identified Themes

Theme	Frequency
Enhanced Customer Engagement	**High**
Streamlined Operations	**High**
Compliance Automation	**Moderate**

Theme	Frequency
Faster and More Accurate Processes	**High**
Educating Employees on AI Benefits	**Moderate**

Word Cloud Insights



Exploratory Factor Analysis - Initial Loadings

Correlation Matrix[a]

		Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22	Q23	Q24	Q25	Q26
Correlation	Q5	1,000	,820	,616	,815	,688	,600	,695	,703	,703	,629	,757	,676	,617	,628	,741	,626	,668	,686	,603	,731	,681	,646
	Q6	,820	1,000	,802	,932	,842	,810	,895	,886	,884	,757	,860	,886	,840	,847	,864	,607	,641	,707	,626	,912	,923	,857
	Q7	,616	,802	1,000	,755	,721	,699	,735	,759	,737	,609	,713	,759	,741	,749	,668	,484	,501	,567	,516	,756	,790	,704
	Q8	,815	,932	,755	1,000	,866	,769	,846	,857	,842	,731	,896	,869	,802	,811	,835	,623	,678	,715	,645	,840	,856	,779
	Q9	,688	,842	,721	,866	1,000	,812	,899	,880	,924	,773	,732	,839	,818	,748	,843	,560	,668	,690	,643	,876	,879	,802
	Q10	,600	,810	,699	,769	,812	1,000	,853	,806	,866	,661	,672	,786	,743	,709	,791	,436	,479	,486	,526	,805	,858	,788
	Q11	,695	,895	,735	,846	,899	,853	1,000	,949	,962	,806	,737	,873	,850	,769	,892	,505	,633	,620	,614	,905	,913	,894
	Q12	,703	,886	,759	,857	,880	,806	,949	1,000	,931	,801	,747	,890	,862	,790	,856	,460	,551	,599	,579	,879	,899	,867
	Q13	,703	,884	,737	,842	,924	,866	,962	,931	1,000	,810	,719	,855	,825	,752	,885	,498	,609	,592	,584	,896	,919	,869
	Q14	,629	,757	,609	,731	,773	,661	,806	,801	,810	1,000	,632	,740	,710	,646	,771	,483	,588	,580	,561	,747	,769	,804
	Q15	,757	,860	,713	,896	,732	,672	,737	,747	,719	,632	1,000	,857	,825	,874	,767	,629	,693	,694	,614	,759	,766	,702
	Q16	,676	,886	,759	,869	,839	,786	,873	,890	,855	,740	,857	1,000	,952	,924	,855	,540	,611	,681	,610	,886	,911	,843
	Q17	,617	,840	,741	,802	,818	,743	,850	,862	,825	,710	,825	,952	1,000	,942	,826	,548	,613	,666	,569	,847	,854	,818
	Q18	,628	,847	,749	,811	,748	,709	,769	,790	,752	,646	,874	,924	,942	1,000	,788	,632	,631	,682	,591	,827	,847	,789
	Q19	,741	,864	,668	,835	,843	,791	,892	,856	,885	,771	,767	,855	,826	,788	1,000	,633	,692	,700	,603	,899	,848	,859
	Q20	,626	,607	,484	,623	,560	,436	,505	,460	,498	,483	,629	,540	,548	,632	,633	1,000	,834	,812	,738	,603	,530	,535
	Q21	,668	,641	,501	,678	,668	,479	,633	,551	,609	,588	,693	,611	,613	,631	,692	,834	1,000	,785	,707	,659	,589	,568
	Q22	,686	,707	,567	,715	,690	,486	,620	,599	,592	,580	,694	,681	,666	,682	,700	,812	,785	1,000	,790	,751	,637	,625
	Q23	,603	,626	,516	,645	,643	,526	,614	,579	,584	,561	,614	,610	,569	,591	,603	,738	,707	,790	1,000	,648	,628	,609
	Q24	,731	,912	,756	,840	,876	,805	,905	,879	,896	,747	,759	,886	,847	,827	,899	,603	,659	,751	,648	1,000	,926	,900
	Q25	,681	,923	,790	,856	,879	,858	,913	,899	,919	,769	,766	,911	,854	,847	,848	,530	,589	,637	,628	,926	1,000	,895
	Q26	,646	,857	,704	,779	,802	,788	,894	,867	,869	,804	,702	,843	,818	,789	,859	,535	,568	,625	,609	,900	,895	1,000
Sig. (1-tailed)	Q5		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	Q6	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q7	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q8	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q9	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q10	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q11	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q12	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q13	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q14	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q15	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q16	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q17	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000	,000
	Q18	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000	,000
	Q19	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000	,000
	Q20	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000	,000
	Q21	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000	,000
	Q22	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000	,000
	Q23	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000	,000
	Q24	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000	,000
	Q25	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000		,000
	Q26	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	

a. Determinant = 9.75E-019

KMO and Bartlett's Test

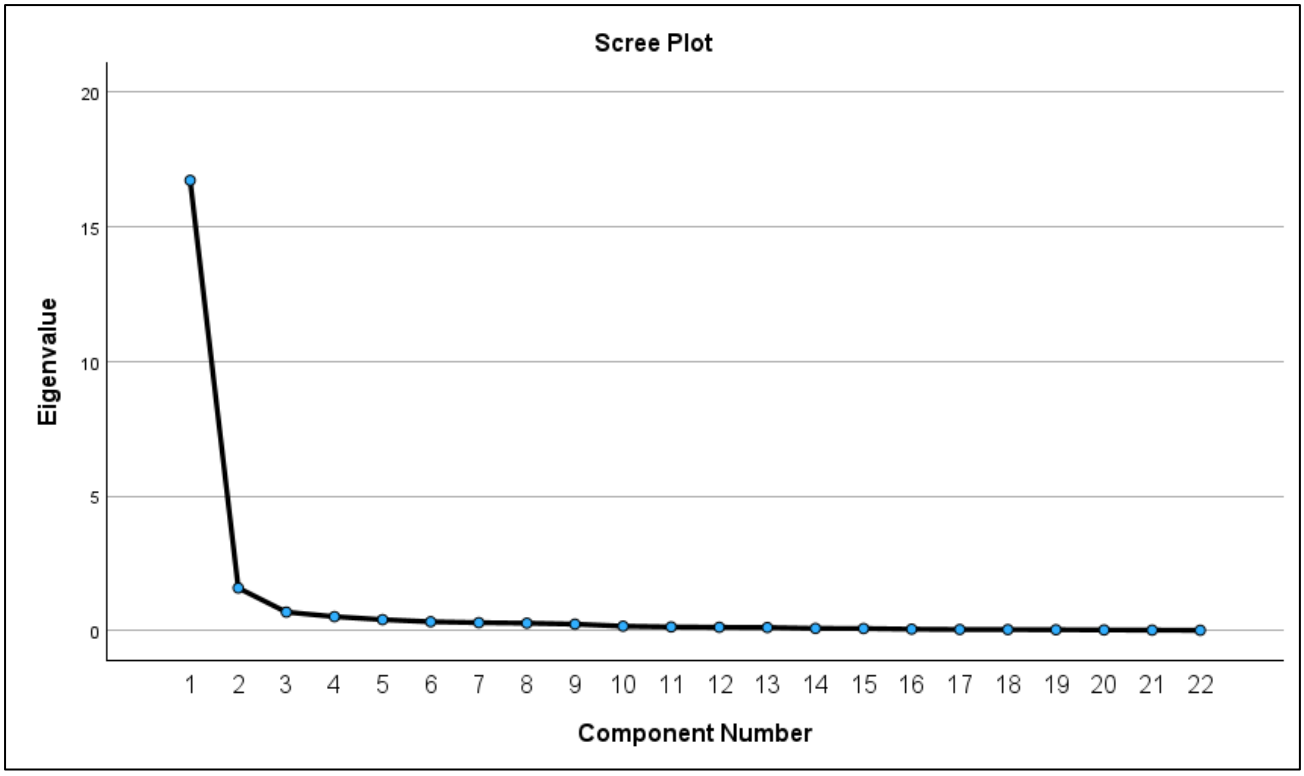
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,941
Bartlett's Test of Sphericity	Approx. Chi-Square	3020,502
	df	231
	Sig.	<.001

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	16,725	76,023	76,023	16,725	76,023	76,023	16,249
2	1,585	7,203	83,226	1,585	7,203	83,226	11,789
3	,687	3,124	86,350				
4	,520	2,362	88,712				
5	,408	1,856	90,568				
6	,330	1,499	92,067				
7	,297	1,350	93,417				
8	,277	1,260	94,677				
9	,241	1,097	95,773				
10	,166	,753	96,526				
11	,137	,625	97,151				
12	,125	,566	97,717				
13	,115	,525	98,242				
14	,083	,375	98,617				
15	,078	,355	98,972				
16	,055	,249	99,222				
17	,043	,194	99,416				
18	,039	,175	99,591				
19	,033	,151	99,742				
20	,025	,115	99,857				
21	,019	,084	99,941				
22	,013	,059	100,000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.



Component Matrix[a]

	Component 1	Component 2
Q5	,798	,205
Q6	,955	
Q7	,806	-,125
Q8	,930	
Q9	,918	
Q10	,841	-,284
Q11	,939	-,207
Q12	,925	-,252
Q13	,930	-,232
Q14	,818	-,107
Q15	,870	,124
Q16	,938	-,124
Q17	,907	-,110
Q18	,890	
Q19	,923	
Q20	,682	,641
Q21	,742	,528
Q22	,778	,505
Q23	,721	,453
Q24	,947	
Q25	,943	-,192
Q26	,902	-,169

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Pattern Matrix[a]

	Component 1	Component 2
Q5	,406	,486
Q6	,843	,153
Q7	,796	
Q8	,724	,265
Q9	,841	,110
Q10	1,008	-,185
Q11	,998	
Q12	1,038	-,118
Q13	1,019	
Q14	,785	
Q15	,557	,391
Q16	,901	
Q17	,860	
Q18	,712	,230
Q19	,778	,192
Q20	-,193	1,062
Q21		,920
Q22		,897
Q23		,811
Q24	,837	,150
Q25	,983	
Q26	,924	

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 3 iterations.