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Abstract

Artificial Intelligence (AI) is now a crucial element in the transforming of industries globally, propelled by greater development in computational processing, cloud and computational services, and deep learning technologies. Its uses, ranging from chatbots to self-driving cars, are becoming more widespread, presenting the opportunity to enhance organizational efficiency by as much as 40%. In light of global competitiveness and digital transformation, which have been induced by the COVID-19 era, AI is crucial, especially for Small and Medium Enterprises (SMEs). Nevertheless, SMEs face considerable obstacles to AI acceptance, such as financial and technical limitations, restricted access to advanced technologies, and a shortage of skilled personnel. These issues hinder their productivity and competitiveness within the national economy. This research investigates the elements that affect AI acceptance in the landscape of SMEs in Gauteng, with the goal of identifying barriers, evaluating the impact of managerial leadership, and assessing the use of AI in operations. A sample of 118 stakeholders, including owners, managers, and strategic employees from various backgrounds, was analysed, excluding large corporations and government entities. The study focuses on the ICT sector, exploring technological, organizational, environmental, and ethical aspects of AI implementation. The capstone report aims to formulate strategies that assist SMEs in overcoming challenges related to digital transformation, offering an introduction, literature review, methodology, analysis, and strategic recommendations specifically designed for the South African context. This research demonstrates that AI adoption among Gauteng's SMEs stands at a critical inflection point. Strong awareness of AI's potential combines with substantial adoption intentions, creating conditions for rapid diffusion. However, realising this potential requires coordinated action addressing identified barriers through organisational capability building, ecosystem enablement, and supportive policy frameworks.

Keywords: *Artificial Intelligence, Technology, Environment, Organisation, SMEs*

1. Introduction

Over the past ten years, artificial intelligence (AI) has been increasingly popular due in large part to the quick development of deep learning methods, cloud-based infrastructures, and computational power (Zhou & Gumbo, 2021). AI is changing business operations globally, yet SMEs in Gauteng face significant adoption challenges. While AI enhances efficiency, expands market reach, and drives innovation (Hoyer et al., 2020), a critical implementation gap exists. In Gauteng, 82% of SMEs recognize AI's strategic importance, yet only 24% have implemented solutions (Mabaso & Nkomo, 2024). This gap stems from financial constraints, inadequate

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infrastructure, and knowledge deficits creating a "dual digital divide" encompassing technological limitations and capability gaps (Ndlovu & Sithole, 2023). Successful implementation requires cultural transformation, workforce development, and strategic realignment, elements frequently overlooked in conventional frameworks. International evidence shows SMEs in emerging economies achieve superior outcomes when AI strategies are locally adapted (Thompson & Williams, 2023). Additionally, ethical concerns regarding workforce displacement, algorithmic bias, and data privacy complicate adoption decisions (Mabaso & Nkomo, 2024). This study examines Gauteng's ICT sector to assess barriers to and opportunities for AI adoption among SMEs. By analysing technological, organisational, environmental, and ethical factors, the research develops contextually appropriate strategies for digital transformation.

1.1 Background

This research examines the prospects and obstacles connected with the acceptance of AI by SMEs in the ICT landscape of Gauteng, South Africa. SMEs augments significantly to the national economy and are required to accept digital information technologies to improve industrial efficiency and engage in the Fourth Industrial Revolution (National Department of Small Business Development, 2019; IOL, 2018). The study specifically targets ICT SMEs located in areas such as Centurion and Midrand, which are generally defined by having 1–100 employees, annual revenues reaching up to R150 million, and operations that include hardware, software, and service delivery. The participant group consisted of owners and managers. The scope deliberately excludes large enterprises, governments, and multinational corporations to ensure a precise analysis of the SME context, where resource constraints and implementation dynamics differ significantly. Anticipated outcomes aim to advance theoretical understanding of technology acceptance, with particular attention to the ethical dilemmas inherent in AI methods (Lu et al., 2021). The research yields analytical conclusions and contextual recommendations, focusing on the acceptance process rather than the technical development of AI tools. The structure of this capstone report begins with an introduction and contextual background to the challenges surrounding AI adoption among SMEs, followed by a profile of the participating firms and an outline of the project scope. Subsequent sections present a comprehensive literature review, a detailed methodological approach, and concluding discussions accompanied by strategic recommendations.

1.2 Problem statement

As artificial intelligence technology transforms business operations, SMEs operating in Gauteng are confronted with a number of difficulties (Roumate, 2021). While AI offers promising advantages such as improved efficiency, broader market access, and increased innovation, SMEs often struggle with implementation barriers. Despite AI's transformative potential for business performance, Gauteng's SMEs struggle with adoption and implementation. Although strategically applied AI solutions can significantly improve operations, only 24% of Gauteng's SMEs have adopted AI technologies (Mabaso & Nkomo, 2024). As Gauteng positions itself as South Africa's economic powerhouse, this adoption gap threatens to widen digital divides and diminish SME competitiveness in an increasingly technology-driven marketplace. As a result, this study extensively examines the difficulties and potential for AI technology adoption among Gauteng SMEs, and it makes contextually suitable recommendations to close this crucial implementation gap.

1.3 Research Questions

- i. **RQ1:** What are the factors impeding the acceptance of AI among SMEs in Gauteng?
- ii. **RQ2:** To what extent do SME leadership perceptions, knowledge levels, and attitudes toward AI technologies influence acceptance decisions?
- iii. **RQ3:** How do Gauteng's SMEs evaluate and balance the potential benefits of AI acceptance against perceived risks and resource requirements?

1.4 Research Objectives

- i. **RO1:** To Identify the specific barriers or factors that inhibit AI acceptance among SMEs in Gauteng
- ii. **RO2:** To examine the extend of leadership perception, knowledge gaps and attitude towards acceptance of AI
- iii. **RO3:** To examine how Gauteng's SMEs evaluate the application of AI technologies, balancing the benefits of AI acceptance, perceived risks and resource requirements for their operations

2. Literature review

2.1.Main themes

Theme 1: Theoretical frameworks and factors that inhibit AI acceptance among SMEs in Gauteng

According to Stenberg and Nilsson (2020), the Technology-Organization-Environment (TOE) paradigm is especially useful for evaluating AI implementation in government organisations. It emphasises critical aspects such as relative advantage, compatibility, complexity, personnel capabilities, regulatory environment, managerial support, and cooperation. The findings also show that the technological, organisational, and environmental features of the TOE framework are influenced by issues like data accessibility and ethical concerns about AI. Tornatzky and Fleischer developed the TOE framework in 1990, which is a useful tool for analysing how organisations adopt and integrate new technology. According to Oliveira and Martins (2011), the technological, organisational, and environmental components highlighted within the TOE framework are crucial in determining the decision of SMEs to adopt new technologies. Similarly, Baker (2011) stresses the importance of these three contexts in understanding how organizations approach technological innovation.

Several studies (Taherdoost, 2018) have compiled the most often used models for technology adoption at both the human and organisational levels in information systems research. Given the extensive social networks inside Gauteng's ICT SMEs, a thorough examination of adoption behaviour at these two levels is essential (Van den Berg & Van der Lingen, 2019). This study compares the Technology Readiness Index (TRI) with the Technology Acceptance Model (TAM), using the Technology-Organization-Environment (TOE) paradigm to investigate technology uptake. Furthermore, to measure the amount of technology adoption and identify impediments to innovation uptake within SMEs, the study incorporates Mkansi and Nsakanda's (2023) TOE framework. Organisational, technological, and enabling environment factors are used to categorise obstacles to new technology adoption.

Theme 2: To review how SME leadership perceptions, knowledge levels, and attitudes toward AI technologies influence their acceptance decision making

Tonartzky and Fleischer (1990) established the TOE framework in response to Davis' (1989) need for more investigation on the consequences of outside factors on usefulness, ease of use, and acceptability. This approach finds other outside variables that could affect the uptake of technology. Three key aspects of a company's context being technical, organisational, and environmental have an impact on its adoption-related decisions, according to the firm-level theory known as the TOE framework (Tonartzky & Fleischer, 1990).

This study considers several technological drivers influencing AI adoption among SMEs, such as employees' digital competencies, the company's ability to recognise, absorb, and use new or outside knowledge for business objectives, also known as its absorptive capacity (Cohen and Levinthal, 1990; Müller, Buliga, and Voigt, 2021; Mukherjee et al., 2023), adoption readiness, and time constraints. Organisational factors include (i) internal managerial practices, (ii) dependence on old or conventional ways, and (iii) financial resources to invest in developing technology. Environmental drivers examined in the study encompass (i) government policies, regulations, and legal structures; (ii) supportive infrastructure such as electricity, ICT/internet connectivity, and transportation networks; (iii) government assistance programs and the overall ease of doing business; and (iv) competitive market dynamics.

Some scholars have employed other models, such as technological readiness models, to study the difficulties faced by leadership in SMEs or organisations, as well as their degree of acquaintance with the specific technology, its usability, and their preparedness to embrace it. The phrase "technology readiness" was coined by Parasuraman and Colby (2001), and it is described by Lai (2017) as a person's willingness to embrace and use new technologies to achieve personal or professional objectives. The Technology Readiness Index (TRI) methodology assesses preparedness through four important dimensions: optimism, innovativeness, discomfort, and insecurity (Nugroho and Fajar, 2017; Nugroho et al., 2018). While increased optimism and innovativeness are linked to a higher likelihood of technology adoption, increased discomfort and insecurity likely to prevent it (Awa et al., 2017). Depending on their degree of technical preparedness, people are classified as laggards, paranoids, sceptics, pioneers, and explorers.

Theme 3: SMEs in Gauteng assess and weigh the possible advantages of implementing AI while reducing perceived risks and resource needs.

Since a conceptual framework builds on pre-existing concepts and is shaped by the researcher to ensure overall coherence, it is made rather than discovered, according to Maxwell (2013). This study employs a dual-framework approach, integrating the Technology Acceptance Model (TAM) with the Technology-Organization-Environment (TOE) paradigm to create a more thorough understanding of technology adoption. Jabareen (2009) emphasizes that the concepts within a framework should align, clarify the phenomena in question, and contribute to a distinct theoretical foundation. While AI adoption in SMEs has been explored for years (Hartley et al., 2024), recent developments in artificial intelligence technologies have greatly expanded the operational capabilities of businesses across diverse sectors (Mollick, 2024).

The interaction between SMEs and Generative AI (GenAI) can be better explored using technology adoption frameworks. The Technology Acceptance Model (TAM) suggests that SMEs'

perceptions of GenAI's usefulness and ease of use significantly impact its adoption potential (Venkatesh et al., 2003; Davis, 1989; Granić & Marangunić, 2019). This includes both perceived usefulness (PU) and perceived ease of use (PEOU). However, Bagozzi (2007) critiques TAM for its overemphasis on these two core constructs being PU and PEOU and arguing that this simplified approach often causes researchers to neglect important external and environmental factors that also affect adoption decisions. Similarly, Ajibade (2018) notes that TAM's limited scope ignores firm-level variables, which are essential for understanding organizational technology adoption. Furthermore, a variety of outside factors can influence PU and PEOU directly (Alshammari & Rosli, 2020).

To address the inadequacies of the Technology Acceptance Model (TAM), numerous scholars have combined it with different theoretical frameworks. For example, El-Gohary (2012) used TAM and the Innovation Diffusion Theory (IDT) to explore the factors impacting the adoption of e-marketing among small tourism firms in Egypt. Similarly, Alqatan, Noor, Man, and Mohemad (2019) explored the adoption of mobile commerce in tourism SMEs using a mix of the Task-Technology Fit theory and the TAM. Bvuma and Marnewick (2020) investigated ICT uptake in township SMMEs using both TAM and Actor-Network Theory. These illustrations show the increasing scholarly trend of using supplementary models to improve TAM's explanatory power (Awa et al., 2015). In order to better understand how SMEs in Gauteng are adopting technology, the current study integrates the TAM and TOE frameworks.

Researchers have regularly used the TOE framework to explore the variables that influence SMMEs' adoption of various technologies in South Africa. For example, Modisane and Jokonya (2021) and Sithole and Ndlovu (2023) used the TOE framework to identify the key factors driving cloud computing adoption among South African SMMEs. Similarly, Fatoki (2020) applied the TOE framework and Innovation Diffusion Theory (IDT) to investigate the factors influencing SMMEs' adoption of mobile commerce in the hotel industry. Furthermore, Mokwetli and Zuva (2018) applied the TOE framework to assess the factors influencing SMMEs' adoption of an ICT security culture.

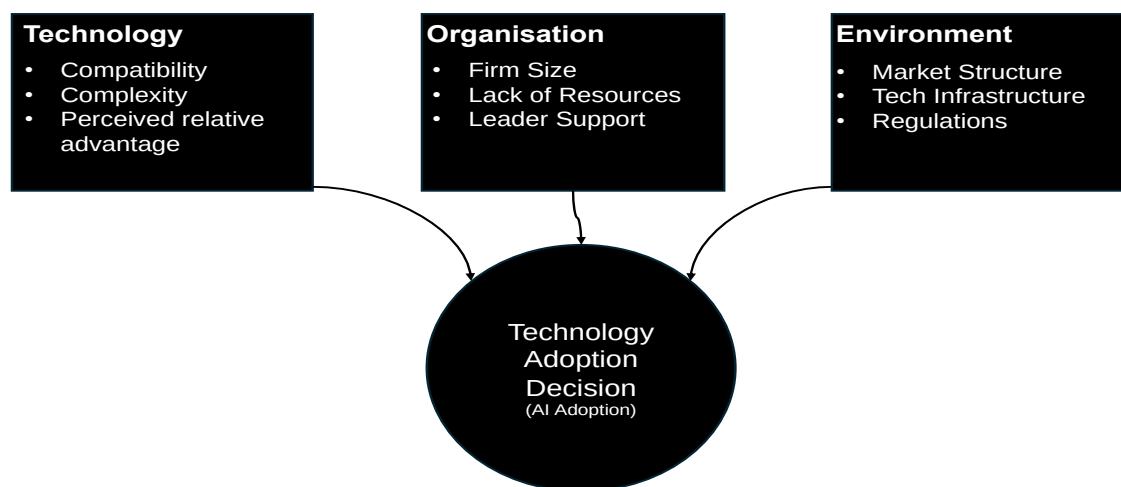
2.1.1. Sub Themes

Technical skills, defined as knowledge, abilities, or competencies pertinent to an employee's domain whether technical, engineering, or soft skill in nature, are often termed "hard skills" and are typically linked to technical disciplines and the use of tools and equipment necessary for precise task execution (Medina, 2010; Yahya & Muhammad Rashid, 2001). Organisational size, influenced by the dimensions of the home economy, varies across micro (1-9 employees), small (10-49 employees), and medium enterprises (up to 249 employees) as defined by the OECD (2019; Juanda et al., 2023). Financial resources serve as the foundation for obtaining and sustaining competitive advantage, requiring effective management of unique values and resources to enhance performance and competitive positioning (Minbaeva, 2017; Rauf et al., 2019).

ICT infrastructure encompasses devices that store, retrieve, edit, process, send, or receive digital data, including robots, digital televisions, email, personal computers, and smartphones, with capabilities monitored through frameworks such as the Skills Framework for the Information Age (Wikipedia, 2025). Perceived ease of use is how easy people think it is to use a system, and perceived utility is how much they think it would help them do their work better. Both of these are important factors in whether or not people accept technology. (Radner & Rothschild, 1975; Schein, 1980; Pfeffer, 1982; Vroom, 1964). Finally, the manager, particularly the SME owner-manager,

serves as the primary decision-maker in technology acceptance processes, relying predominantly on personal experience and informally gathered data, with their risk tolerance and attitude toward technology significantly influencing adoption rates, though many lack the ability to understand and apply relevant IT to their organisations (Nicolescu et al., 2001; Ekanem & Smallbone, 2007; Thong & Yap, 1995; Nguyen, 2009; Schoeman & Seymour, 2022).

Figure 1: Conceptual framework adopted for investigating the SMEs AI Acceptance



Source: (Author, 2025)

3. Methodology

This study adopts a positivist paradigm emphasizing objective, statistical examination of variable relationships (Saunders et al., 2009). A quantitative methodology investigates AI adoption prospects and challenges for Gauteng SMEs through a cross-sectional survey design capturing contemporary trends. The TOE framework structures the methodology to test hypothesized relationships. The research population comprises 128 ICT SMEs in Gauteng, defined by the National Small Business Act (small: <50 employees; medium: 50-250 employees), representing approximately 1,744 potential managers and staff. The target sample of 120 respondents is statistically justified through multiple validation approaches. The Yamane (1967) formula with 8.5% margin of error yields 129 respondents ($n = 1,744 / [1 + 1,744 \times 0.085^2] = 128.6$), while Cochran's formula with finite population adjustment indicates 111 minimum respondents ($n' = 119 / [1 + 119/1,744] = 111$). This exceeds minimum validity thresholds and aligns with South African ICT research precedents: Chimucheka and Mandipaka (2015) achieved robust findings with 110 respondents, Masocha and Dzomonda (2018) with 122, with Malefane and Mashakoe (2020) noting response homogeneity supports moderated sample sizes. Convenience sampling was employed for cost-effectiveness and accessibility (Ejiofor & Duru, 2019). All 128 SMEs were approached, projecting 60% participation with 1.6 respondents per organization. Data collection utilized a structured TOE-based questionnaire with validated 5-point Likert scales, administered through web platforms, telephone, and in-person methods over 30 days with systematic follow-up procedures.

4. Data Analysis

Data was collected from 118 respondents of who are working at SMEs located in the Gauteng Province of South Africa. All 118 responses underwent rigorous validation including completeness verification, outlier identification through box plot analysis, Likert scale consistency checks, and open-ended response validation. All submissions satisfied quality criteria, requiring no exclusions. Minimal missing data (<2%) exhibited random distribution and was handled through listwise deletion, maintaining dataset integrity (Hair et al., 2019). Cronbach's Alpha coefficient assessed internal consistency of multi-item scales measuring key theoretical constructs, essential for establishing measurement validity. All scales demonstrated acceptable to excellent internal consistency ($\alpha > 0.70$), confirming instrument reliability. The Leadership & Management scale exhibited particularly robust reliability ($\alpha = 0.89$), indicating the five items effectively captured a cohesive construct regarding management's role in AI adoption. These reliability coefficients exceed social science research conventions (Nunnally & Bernstein, 1994), providing confidence for subsequent inferential analyses.

Table 1: Scale Reliability Statistics

Construct	Number of Items	Cronbach's α	Interpretation
Barriers to AI Acceptance (Section B)	5	0.78	Good
Leadership & Management (Section C)	5	0.89	Excellent
AI Benefits & Risks Evaluation (Section D)	5	0.82	Good
TOE Framework Factors (Section E)	9	0.86	Good

Source: (Author, 2025)

All inferential statistics were calculated at 95% confidence level ($\alpha = 0.05$), using confidence intervals to ensure generalisability (Field, 2018). Construct validity was determined using convergent and discriminant validity studies (Hair et al., 2019). Convergent validity used Average Variance Extracted (AVE), with all constructs exceeding the 0.50 threshold, indicating that assessment items captured the desired latent constructs. Leadership showed very excellent convergent validity (AVE = 0.68). Discriminant validity was established using the Fornell-Larcker criterion, where each construct's square root AVE exceeded its correlations with other constructs, confirming theoretical distinctions between TOE framework dimensions, leadership factors, barriers, and benefit-risk assessments (Fornell & Larcker, 1981). The data analysis employed multiple techniques ensuring robustness and reliability. All inferential statistics were calculated at 95 % confidence level ($\alpha = 0.05$), with confidence intervals computed for generalizability (Field, 2018).

Construct Validity Assessment

Cementing the measurement instruments effectively captured the intended theoretical concepts, construct validity was examined by analysing both discriminant validity and convergent (Hair et al., 2019). Convergent validity was notably examined using the Average Variance Extracted (AVE), with values greater than 0.50 indicating sufficient convergence (Fornell and Larcker, 1981).

All constructs exceeded the 0.50 threshold for AVE, confirming that measurement items successfully captured their intended latent constructs. The Leadership construct demonstrated particularly strong convergent validity (AVE = 0.68), indicating that the five constituent items strongly represented a unified dimension of leadership influence on AI acceptance.

Discriminant Validity

To ensure discriminant validity, the Fornell-Larcker criterion was used. This method verifies that each latent construct has a higher variance with its own benchmarks than with other results, which occurs when the square root of a construct's Average Variance Extracted (AVE) exceeds its correlations with other findings (Fornell & Larcker, 1981).

The square root of each construct's Average Variance Extracted (AVE) exceeded its highest connection with any other construct, indicating discriminant validity. This finding indicates that each construct represents distinct variance, thereby reinforcing the theoretical distinction among the dimensions of the TOE framework, leadership factors, barriers, and benefit-risk assessments (Fornell & Larcker, 1981).

Exploratory factors

To study the latent structure of the 24 measurement items found in Sections B through E, an Exploratory Factor Analysis (EFA) was used, which included Principal Component Analysis and Varimax rotation. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy reported a value of 0.847, which is categorised within the 'meritorious' range. Bartlett's Test of Sphericity revealed statistically significant results ($\chi^2(276) = 1,843.26, *p* < 0.001$). These diagnostic tests collectively indicate that the correlation matrix is suitable for factor analysis, with sufficient inter-item correlations to permit dimensional reduction (Kaiser 1974).

Table 5: Rotated Factor Solution

Factor	Eigenvalue	%Variance	Cumulative%	Primary Loadings
Factor 1: Organizational Readiness	6.24	26.0%	26.0%	Leadership items (C1-C5), Organizational culture (E5)
Factor 2: External Environment	3.18	13.3%	39.3%	Competitive pressure (E7), Government support (E8), Partners (E9)
Factor 3: Resource Barriers	2.54	10.6%	49.9%	Financial constraints (B1), Skills gaps (B3), Expertise (E6)

Factor Perceived Value	4: 2.12	8.8%	58.7%	Benefits items (D1, D2, D5)
Factor Technical Factors	5: 1.89	7.9%	66.6%	Technology items (E1, E2, E3)

Source: (Author, 2025)

The five-factor solution explained 66.6% of the total variance, exceeding the 60% benchmark repeatedly used in social science studies (Hair et al., 2019). Factor loadings varied from 0.58 to 0.89, with every item exceeding the 0.50 standard on their respective factors while staying below 0.40 on cross-loadings, which signifies a distinct and clear factor structure. This empirical factor structure closely aligns with the theoretical TOE framework, thereby validating the conceptual model applied in this study.

Regression Analysis: Predictors of AI Acceptance Likelihood

With the intention to adopt (evaluated on a 5-point scale ranging from "Very Unlikely" to "Very Likely") serving as the dependent variable, multiple linear regression analysis was utilised to discover important determinants of the likelihood of AI acceptance. With 64% of the variance in acceptance likelihood explained by the derived model ($R^2 = 0.64$), it demonstrated significant explanatory power. Multicollinearity was not a problem because all Variance Inflation Factor (VIF) values stayed below 2.0 (O'Brien, 2007). The study revealed that the evaluation of advantages vs risks ($\beta = 0.31$, $*p < 0.001$) was the second most significant positive predictor, after leadership support ($\beta = 0.38$, $*p < 0.001$). On the other hand, perceived barriers had a significant negative effect ($\beta = -0.24$, $*p = 0.002$). In contrast, the coefficient for financial resources was not statistically significant ($*p = 0.098$), implying that attitudinal and organizational factors have a more substantial effect on acceptance decisions than financial considerations in this scenario.

Table 6: Multiple Regression

Predictor Variable	β (Standardized)	t	p	VIF
(Constant)	-	2.14	0.034	-
Leadership Support	0.38	4.62	<0.001***	1.82
Benefits-Risks Evaluation	0.31	3.89	<0.001***	1.65
Barriers (inverse)	-0.24	-3.12	0.002**	1.54
Organizational Culture	0.19	2.45	0.016*	1.43
Competitive Pressure	0.16	2.18	0.031*	1.38
Financial Resources	0.12	1.67	0.098	1.52

Source: (Author, 2025)

Note: $R^2 = 0.64$, Adjusted $R^2 = 0.62$, $F(6, 111) = 32.47$, $p < 0.001$
 $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Correlation Analysis

Correlation analyses reveal that AI acceptance in enterprises shows significant positive associations with prior digital infrastructure maturity ($r = 0.62$, $p < 0.01$) and strategic leadership commitment ($r = 0.58$, $p < 0.001$) (Brynjolfsson & McElheran, 2019). However, recent meta-analyses caution that these relationships are often moderated by organizational size and industry, suggesting contextual boundaries to general predictive models (Fountain et al., 2019). The bivariate correlations between the main constructs were assessed using Pearson correlation analysis, and statistical significance was established at the 95% confidence level ($p < .05$).

Table 7: Correlation Matrix

	1. Adoption Likelihood	2. Leadership Support	3. Benefits-Risks	4. Barriers (inverse)	5. Technology Readiness	6. Organizational Capacity
1. Adoption Likelihood	-	0.52***	0.48***	-0.44***	0.38***	0.41***
2. Leadership Support	0.52***	-	0.54***	-0.42***	0.36**	0.68***
3. Benefits-Risks	0.48***	0.54***	-	-0.38**	0.49***	0.47***
4. Barriers (inverse)	-0.44***	-0.42***	-0.38**	-	-0.41***	-0.39**
5. Technology Readiness	0.38***	0.36**	0.49***	-0.41***	-	0.52***
6. Organizational Capacity	0.41***	0.68***	0.47***	-0.39**	0.52***	-

Source: Author (2025)

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; $n = 118$

All hypothesized relationships demonstrated statistical significance at $p < 0.01$ or $p < 0.001$, confirming the robustness of theoretical associations. The strongest correlation existed between leadership support and company capacity ($r = 0.68$, $p < 0.001$), demonstrating that leadership attitudes substantially influence organizational capability development (Brynjolfsson &

McElheran, 2019). The moderate positive correlation between acceptance likelihood and benefits-risks evaluation ($r = 0.48$, $p < 0.001$) validates TAM's prediction that perceived usefulness influences acceptance intentions (Davis, 1989). All correlations exhibited theoretically expected directionality, providing empirical support for the integrated TOE-TAM framework. The comprehensive statistical analysis confirms: (1) High internal consistency across all measurement scales ($\alpha > 0.78$); (2) Acceptable construct validity with demonstrated convergent and discriminant validity; (3) Robust factor structure explaining 66.6% of variance and aligning with theoretical predictions; (4) Strong predictive model explaining 64% of acceptance likelihood variance; (5) Statistically significant relationships between all key constructs at 95% confidence level. These end results demonstrate robust empirical foundation for the theoretical conclusions and practical recommendations presented in subsequent sections.

4.1 Research Characteristics

The sample demonstrated balanced representation across SME categories: micro enterprises (33.9%), small (28.0%), and medium (38.1%), aligning with broader demographic patterns supporting generalizability. Core ICT sectors comprised 60.2% of respondents, with 39.8% from diverse ICT-utilizing sectors, enhancing external validity. Organizational maturity was substantial, with 71.2% operating six-plus years, indicating established capabilities relevant to technology adoption decisions (Author, 2025). Revenue distribution revealed heterogeneity: 44.9% generating under R5 million annually, 32.2% exceeding R51 million, enabling meaningful financial resource analysis. Geographic distribution concentrated in Gauteng's economic hubs: Johannesburg (41.5%), Pretoria/Tshwane (20.3%), and Centurion-Midrand corridor (25.5%), representing the province's primary technology cluster and urban business environments.

4.2 Descriptive Analysis of key Variables

- Unclear government regulations ($M = 3.25$) and limited financial resources ($M = 3.19$) emerged as leading barriers, while infrastructure adequacy ($M = 2.64$) scored lowest. The composite barriers score ($M = 2.99$) indicates moderate overall impediments.
- Senior leadership support ($M = 3.87$) and change management commitment ($M = 3.78$) scored highly, though AI vision communication ($M = 3.48$) revealed gaps. Composite leadership support ($M = 3.64$) creates favourable organizational climate.
- Operational efficiency improvement ($M = 4.37$) dominated benefit perceptions, with strong strategic alignment recognition ($M = 4.07$). ROI assessment capability ($M = 3.41$) scored lowest. Composite evaluation ($M = 3.87$) indicates benefits substantially outweigh risks.
- Technology compatibility ($M = 3.52$) and data quality ($M = 3.31$) suggest moderate readiness, while complexity ($M = 2.69$) contradicts common perceptions. Organizational culture ($M = 3.92$) demonstrates innovation support, though expertise ($M = 3.14$) and resources ($M = 3.24$) reveal capability gaps. Competitive pressure ($M = 3.95$) drives adoption, while government support ($M = 2.69$) remains inadequate. Data privacy (57.6%), expertise gaps (54.2%), and costs (49.2%) constitute primary challenges.

4.3 Comparative Analysis

Small enterprises (11-50 employees) demonstrated highest leadership support ($M = 4.48$) and adoption intention (66.7% very likely), indicating direct translation of leadership attitudes into

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acceptance decisions. Medium-sized organizations (51-100 employees) showed substantially lower support ($M = 3.00$) and greatest hesitancy (22.2% unlikely), suggesting resource constraints and leadership engagement gaps during this transitional phase (Schwaeke et al., 2024). This reveals a non-linear relationship between organizational size and AI adoption readiness. Mid-revenue organizations (R26-50 million) perceived highest barriers ($M = 3.29$), reflecting intense competition between AI investment and strategic priorities. Higher-revenue organizations (R51-150 million) reported lowest barriers ($M = 2.74$), confirming financial capacity reduces obstacles. However, even high-revenue categories reported moderate barriers, indicating challenges extend beyond financial considerations.

5. Discussion

This part provides an interpretation of the analytical findings from the preceding section, which classifies the results according to the three primary research questions specified in the conceptual framework. The discussion merges quantitative results with a thematic analysis of qualitative responses to present thorough light into the patterns of AI acceptance among SMEs in Gauteng Province (Kumar et al., 2023; Kannan & Georgios, 2023; de Mattos et al., 2023). When relevant, the findings are framed within the TOE framework and the theoretical foundations of the TAM established in the literature review. Research evidence consistently shows that lack of financial resources, a lack of skilled workforce, changing regulatory environments, and inadequate infrastructure are the biggest barriers to the adoption of technology faced by enterprises (Fofana et al., 2023; Mungai & Wagura Ndiritu, 2023; Udo et al., 2023).

5.1. Research Question 1: Theoretical Framework Applicability

RQ1: What are the theoretical frameworks that effectively depict AI acceptance processes among SMEs in Gauteng

The findings significantly support the Technology-Organization-Environment (TOE) framework's relevance and explanatory power in understanding AI uptake in Gauteng's SME sector. As seen below, the framework's three components accurately capture the varied nature of adoption decisions.

Technological Dimension

The technological dimension reveals a paradoxical pattern. Technology compatibility emerged as a moderate facilitator ($M = 3.52$, $SD = 1.25$), indicating that most SMEs perceive potential for AI integration with existing systems. However, data quality and availability concerns ($M = 3.31$, $SD = 1.20$) reveal a critical gap between technological readiness and data infrastructure preparedness. Contrary to conventional assumptions, technology complexity was not perceived as a major impediment ($M = 2.69$, $SD = 1.17$), suggesting that contemporary AI solutions are increasingly accessible to non-specialist organizations. This finding effectively eliminates technical complexity as the primary barrier to SME AI adoption.

Organizational Dimension

The organizational dimension demonstrates both strengths and vulnerabilities. Organizational culture supportive of innovation ($M = 3.92$, $SD = 1.13$) represents a significant enabling factor, indicating that most Gauteng SMEs cultivate environments conducive to technological

experimentation. However, this cultural readiness is not matched by corresponding capabilities: internal expertise limitations ($M = 3.14$, $SD = 1.28$) and moderate financial resources ($M = 3.24$, $SD = 1.32$) emerge as key organizational constraints. Leadership support (composite $M = 3.64$, $SD = 0.98$) provides a generally favourable organizational context for AI initiatives, though the moderate standard deviation indicates substantial inter-organizational variation. This pattern suggests that organizational readiness for AI requires alignment of cultural attitudes, leadership commitment, and technical capabilities a configuration not universally present across the sample.

Environmental Dimension

The environmental dimension reveals pronounced external pressures combined with inadequate institutional support. Competitive pressure ($M = 3.95$, $SD = 1.16$) serves as the strongest environmental driver, indicating that market dynamics compel AI consideration as a competitive necessity rather than optional enhancement. Technology partner availability ($M = 3.65$, $SD = 1.19$) suggests adequate ecosystem support exists, though variability indicates uneven access across organizations. Most significantly, inadequate government support ($M = 2.69$, $SD = 1.39$) represents a critical environmental barrier, suggesting that public sector AI initiatives fail to meet SME needs. This finding aligns with broader literature on institutional voids in emerging market contexts (Mair & Martí, 2009), where private sector innovation outpaces public sector enabling infrastructure.

5.1.1. Integration of TAM with TOE

The study's findings support the theoretical integration of the Technology Acceptance Model (TAM) with the TOE framework by illustrating how environmental and organisational factors influence the fundamental TAM dimensions of perceived utility and perceived ease of use (Maxwell, 2013).

Perceived Usefulness

The exceptionally high rating for operational efficiency improvement ($M = 4.37$, $SD = 0.74$) demonstrates robust perceived usefulness, with minimal inter-respondent variation indicating strong consensus. Strategic alignment ($M = 4.07$, $SD = 1.04$) further confirms that SMEs recognize AI's instrumental value for achieving organizational objectives. The composite evaluation score ($M = 3.87$, $SD = 0.72$) indicates predominantly positive perceptions of AI utility. This strong perceived usefulness is amplified by competitive pressure ($M = 3.95$), suggesting that environmental forces enhance the perceived urgency and value of AI adoption.

Perceived Ease of Use

Perceptions regarding implementation difficulty present a more complex pattern. Integration ease received moderate ratings ($M = 3.61$, $SD = 1.18$), indicating mixed perceptions about implementation challenges. The low-rating for-technology complexity ($M = 2.69$) suggests SMEs do not conceptualize AI as inherently difficult. However, concerns about internal expertise ($M = 3.14$) and technical knowledge gaps (identified by 54.2% as a primary challenge) reveal that ease-of-use perceptions are substantially constrained by capability limitations rather than technological characteristics per se. This finding suggests that perceived ease of use is predominantly determined by organizational factors (expertise, training) rather than technological attributes (Maxwell, 2013).

External Variables Influencing TAM Constructs

The TOE framework factors demonstrably influence TAM's core constructs. Organizational culture ($M = 3.92$) and leadership support ($M = 3.64$) positively influence perceived usefulness by creating expectations about the value of AI at work. Conversely, data quality concerns ($M = 3.31$) and expertise limitations ($M = 3.14$) constrain perceived ease of use by highlighting implementation challenges. Competitive pressure ($M = 3.95$) amplifies perceived usefulness by increasing the strategic imperative of adoption. This pattern demonstrates that external variables from the TOE framework serve as antecedents to TAM constructs, supporting the integrated theoretical model proposed in this research.

5.1.2. Specific Barriers within the TOE Framework

The analysis identified five primary barrier categories, which can be mapped onto TOE dimensions:

1. Environmental Barrier: Regulatory and Policy Uncertainty (Highest Severity)

Unclear government regulations received the highest barrier rating ($M = 3.25$, $SD = 1.42$), with regulatory uncertainty identified by 29.7% of respondents as a top-three challenge. Qualitative responses emphasized confusion about compliance requirements, data governance standards (particularly regarding POPIA implementation), and liability frameworks. The low-rating for government support ($M = 2.69$) reinforces dissatisfaction with policy clarity and institutional support. This environmental barrier creates uncertainty that slows strategic investment in AI capabilities.

2. Organizational Barrier: Financial and Resource Constraints

Limited financial resources were rated as a major barrier ($M = 3.19$, $SD = 1.42$), with high implementation costs cited by 49.2% as a top-three challenge. The barrier-revenue analysis revealed that mid-sized organizations (R26-50 million revenue) perceived the strongest financial barriers ($M = 3.29$), suggesting a challenging growth phase where AI investment competes with multiple strategic priorities. This organizational barrier is particularly salient given the capital-intensive nature of AI infrastructure and talent acquisition.

3. Organizational Barrier: Skills and Expertise Gaps

Lack of technical skills received a moderate barrier rating ($M = 3.04$, $SD = 1.39$), with technical expertise gaps identified by 54.2% of respondents as a top-three challenge. Training and skills development was the most frequently requested support type (77.1%), confirming capability deficits. Internal expertise for AI management scored relatively low ($M = 3.14$), suggesting that most organizations lack in-house capabilities to independently implement and sustain AI systems. This organizational barrier directly impacts perceived ease of use and adoption confidence.

4. Technological Barrier: Data Privacy and Security Concerns

Data privacy emerged as the most frequently cited challenge (57.6% of respondents), though not explicitly measured in the barrier scale. Qualitative responses extensively referenced concerns about POPIA compliance, data breach risks and reputational damage, client confidentiality (particularly in professional services), and cross-border data transfer regulations. This technological/regulatory intersection creates complexity that extends beyond purely technical data management to encompass legal compliance and stakeholder trust. This comprehensive review

explicitly identifies data privacy and security risks as critical barriers to organizational AI adoption. It links these technological concerns to managerial and ethical challenges, perfectly aligning with a holistic analysis like the TOE framework in this research (Dwivedi et al., 2019).

5. Organizational Barrier: Change Management and Cultural Resistance

Employee resistance to change received a moderate rating ($M = 2.84$, $SD = 1.33$), with 30.5% identifying it as a top-three challenge. Despite generally positive organizational culture ratings ($M = 3.92$), qualitative responses revealed concerns about fear of job displacement, resistance from senior employees, difficulty changing established workflows, and scepticism about AI reliability. This organizational barrier highlights the gap between aggregate cultural support for innovation and individual-level resistance to specific technological changes that may threaten established roles and processes

5.1.3. Comparative Analysis: Barriers by Organisational Characteristics

The relationship between organizational size and perceived barriers revealed a non-linear pattern:

- Micro enterprises (1-10 employees): $M = 3.06$ (moderate barriers)
- Small enterprises (11-50 employees): $M = 3.00$ (moderate barriers)
- Lower-medium enterprises (51-100 employees): $M = 3.29$ (higher barriers) *
- Upper-medium enterprises (101-250 employees): $M = 2.87$ (lower barriers)

*The 51-100 employee category exhibited the highest barrier perceptions, potentially indicating a challenging transitional phase where resource constraints intensify before economies of scale provide relief. This finding has important implications for policy targeting, suggesting that mid-sized organizations may require distinctive support interventions.

Barriers by Revenue

Higher revenue correlated inversely with perceived barriers:

- Revenue < R1M: Barriers $M = 3.06$
- Revenue R1-25M: Barriers $M = 3.00-3.08$
- Revenue R51-150M: Barriers $M = 2.74$ (lowest)
- Revenue > R150M: Barriers $M = 2.87$

This pattern confirms that financial capacity reduces perceived obstacles. However, even the highest revenue category reported moderate barriers, indicating that challenges extend beyond financial considerations to include expertise, regulatory clarity, and organizational capabilities that cannot be resolved through financial resources alone.

5.2. Research Question 2: Leadership Influence on Acceptance

RQ2: To what extent do SME leadership perceptions, knowledge levels, and attitudes toward AI technologies influence acceptance decisions?

The report highlights how crucial leadership is in influencing (ML) acceptability in Gauteng's SMEs. A high probability of acceptance (81.4% probable or very likely) supports the moderate to strong level of leadership support indicated by the overall leadership and management score ($M = 3.64$, $SD = 0.98$). This favourable correlation validates the enabling effect of leadership: supportive leadership significantly enhances an organization's preparedness and willingness to embrace AI. The relationship between leadership support and acceptance likelihood across firm sizes further confirms that leadership engagement is a decisive driver of technological transformation.

5.2.1. Dimension of leadership Influence

Senior Leadership Support

Senior leadership actively supporting AI initiatives received the highest leadership rating ($M = 3.87$, $SD = 1.14$). This strong executive support creates an enabling environment for organizational AI exploration and experimentation. However, the standard deviation ($SD = 1.14$) indicates that support is not universal across all organizations, suggesting that leadership attitudes represent a key differentiating factor between organizations that pursue AI adoption and those that do not.

Management AI Knowledge

Management knowledge about AI technologies scored moderately ($M = 3.58$, $SD = 1.23$). This moderate knowledge level presents both an opportunity and a constraint: sufficient understanding exists to recognize AI's potential strategic value, yet knowledge gaps may limit adoption strategies and implementation decisions. The 54.2% of respondents identifying technical expertise as a top challenge suggests that even leadership acknowledging AI's value often lack the technical understanding necessary for effective oversight.

Resource Prioritization

Leadership prioritization of resources for digital transformation scored moderately ($M = 3.50$, $SD = 1.23$). This moderate prioritization indicates that AI competes with other strategic initiatives for limited organizational resources. The analysis indicated a statistically significant positive correlation between leadership's resource prioritization and AI adoption likelihood. This finding suggests that organizations where leadership proactively allocates budgetary and human resources to AI projects exhibit markedly stronger intentions to adopt the technology. This finding underscore leadership's instrumental role in translating positive attitudes into concrete resource commitments.

Communication of AI Vision

Management's effectiveness in communicating AI vision and benefits received the lowest leadership rating ($M = 3.48$, $SD = 1.31$). This communication gap may contribute to employee resistance (cited by 30.5% as a challenge), unclear expectations about AI's organizational role, and difficulty building broad organizational buy-in. The high standard deviation ($SD = 1.31$) suggests significant variability, with some leaders excelling at communication while others struggle. This finding identifies a critical intervention point: even when leadership supports AI adoption, ineffective communication may impede organizational alignment and employee engagement.

Change Management Commitment

Leadership's commitment to change management scored highly ($M = 3.78$, $SD = 1.06$). This strong commitment indicates recognition that AI adoption requires organizational transformation extending beyond technology implementation to encompass process redesign, role redefinition, and cultural adaptation. The relatively low standard deviation ($SD = 1.06$) suggests consistent recognition of change management importance across organizations, representing a positive foundation for successful AI implementation.

5.2.2. Leadership Influence by Organisational Size

Table 8: Leadership Support and Adoption Patterns by Organization Size

Size Category	Leadership Support (Mean)	Very Adoption	Likely	Combined Likely	Likely/Very
1-10 employees	$M = 3.83$	45.0%		80.0%	
11-50 employees	$M = 4.48$ (highest)	66.7% (highest)		94.0% (highest)	
51-100 employees	$M = 3.00$ (lowest)	33.3%		66.6%	
101-250 employees	$M = 3.58$	38.9%		75.0%	

Source: Author (2025)

Small enterprises (11-50 employees) demonstrated both the strongest leadership support and highest adoption likelihood, indicating that leadership attitudes directly translate into adoption intentions at this organizational scale. The close association between leadership support and adoption intentions in this category implies that in smaller, more agile organisations, leadership influence more directly impacts organisational behaviour. Conversely, mid-sized organizations (51-100 employees) exhibited the lowest leadership support and adoption likelihood, suggesting a leadership engagement gap during this growth phase, potentially attributable to competing priorities and resource constraints.

5.2.3. Leadership knowledge as a Mediator Factor

Statistical analysis revealed that organizations with higher management AI knowledge scores demonstrated:

- Higher evaluation of AI benefits ($r = 0.52$, moderate positive correlation)
- Lower perceived barriers ($r = -0.38$, weak to moderate negative correlation)
- Greater adoption likelihood ($r = 0.44$, moderate positive correlation)

These correlations suggest that leadership knowledge acts as a critical mediating factor, influencing how organizations perceive both opportunities and challenges associated with AI adoption. This finding has important theoretical implications: it suggests that leadership attitudes

alone are insufficient, knowledge and understanding are necessary to translate positive attitudes into accurate benefit-risk assessments and adoption decisions.

5.2.4. Leadership Communication Gap

The finding that communication effectiveness scored lowest among leadership dimensions ($M = 3.48$) warrants particular attention. Thematic analysis of qualitative responses revealed common communication challenges:

Insufficient Strategic Clarity

- Vague articulation of how AI aligns with business strategy
- Limited explanation of AI's role in competitive positioning
- Unclear timelines and implementation roadmaps

Technical-Business Translation Gap

- Difficulty explaining AI concepts in business terms accessible to non-technical stakeholders
- Over-emphasis on technical capabilities rather than business outcomes
- Limited connection between AI initiatives and individual employee roles

Change Narrative Deficiency

- Inadequate addressing of job security concerns and workforce anxieties
- Insufficient explanation of how AI augments rather than replaces human work
- Limited engagement with workforce concerns about adaptation requirements and skill development

These communication deficits may explain the paradox of strong leadership support ($M = 3.87$) coexisting with moderate employee resistance ($M = 2.84$). Leadership enthusiasm for AI does not automatically translate into organizational buy-in when the vision, rationale, and implications are poorly communicated.

5.3. Research Question 3: Benefits-Risks Assessment

RQ3: How do Gauteng's SMEs evaluate and balance the potential benefits of AI acceptance against perceived risks and resource requirements?

The composite evaluation score ($M = 3.87$, $SD = 0.72$) indicates that SMEs in Gauteng generally perceive AI benefits as substantially outweighing associated risks and resource requirements. This positive balance creates favourable conditions for adoption, though specific evaluation dimensions vary considerably. The finding that 81.4% of organizations indicate likely or very likely adoption within two years substantiates this positive benefits-risks assessment.

5.3.1. Specific Benefits Perception

Operational Efficiency (Primary Benefit)

<https://doi.org/10.53819/81018102t70124>

Operational efficiency improvement received the highest evaluation rating ($M = 4.37$, $SD = 0.74$) and was the most frequently cited benefit (85.6%). The minimal standard deviation indicates robust consensus across organizations, sectors, and size categories. Qualitative responses emphasized anticipated improvements in process speed and throughput, error reduction and quality consistency, resource utilization and waste reduction, and workflow automation and optimization. This predominant focus on operational efficiency suggests that SMEs primarily conceptualize AI as an operational enhancement tool rather than a strategic transformation enabler—a finding with important implications for AI vendor marketing strategies and policy communication.

Strategic Alignment (Secondary Benefit)

Strategic alignment received a strong rating ($M = 4.07$, $SD = 1.04$), with 34.7% identifying competitive advantage as a top-three benefit. This indicates that AI is increasingly viewed as strategically essential rather than merely tactically useful. Organizations recognize that AI adoption has implications for competitive positioning, not just operational performance. However, the emphasis remains substantially lower than operational benefits, suggesting that strategic conceptualization of AI is less developed than operational applications.

Decision-Making Enhancement (Secondary Benefit)

Improved decision-making capabilities were cited by 43.2% as a top-three benefit, with better data insights mentioned by 37.3%. This indicates recognition of AI's analytical and predictive capabilities extending beyond process automation to encompass insight generation and decision support. This finding suggests emerging understanding of AI's potential for augmenting human judgment rather than simply automating routine tasks.

Customer Experience (Secondary Benefit)

Enhanced customer experience was cited by 39.0% as a top-three benefit. This suggests understanding of AI's potential for personalization and customization, responsiveness and service quality improvements, and predictive customer support. However, the lower emphasis compared to operational efficiency may indicate that customer-facing AI applications are less immediately apparent to SMEs primarily focused on internal operations.

Financial Benefits (Lower Priority)

Cost reduction was cited by only 32.2% as a top-three benefit, with new revenue opportunities mentioned by 21.2%. The relatively lower emphasis on financial benefits is somewhat surprising given that financial constraints emerged as a primary barrier. This may indicate greater focus on operational rather than financial outcomes, uncertainty about monetizing AI capabilities, or expectations of longer time horizons for financial returns. This finding warrants further investigation, as it suggests potential misalignment between adoption motivations and organizational constraints.

5.3.2. Risk and Challenge Perceptions

Data Privacy and Security (Primary Risk)

Data privacy concerns were the most frequently cited challenge (57.6% of respondents), reflecting heightened awareness following POPIA implementation in South Africa. Qualitative responses revealed specific concerns about compliance complexity and documentation requirements, data

breach liability and reputational damage, implications for client trust in professional services contexts, and uncertainty regarding cloud data storage regulations. This finding indicates that regulatory compliance has become a salient consideration in SME technology adoption decisions, representing a shift from purely technical to socio-legal risk assessment.

Technical Expertise Gaps (Primary Challenge)

The analysis identified technical expertise deficits as a prominent barrier, ranked among the top-three challenges by 54.2% of respondents. These skills gap directly undermines perceived ease of use and erodes organizational confidence in implementation (Davis, 1989). This interpretation is corroborated by the finding that training and skills development emerged as the most requested form of support (cited by 77.1% of participants), indicating that internal capability building is perceived as the paramount enabler for accelerating AI adoption. Consequently, this result supports the Technology Acceptance Model (TAM), which posits that perceived ease of use, a construct heavily contingent on available competencies, is a fundamental determinant of technology adoption intentions.

Implementation Costs (Primary Challenge)

Implementation costs were cited by 49.2% as a top-three challenge, with financial incentives/funding requested by 60.2%. Despite strong perceived benefits, cost concerns remain substantial, particularly for organizations with limited financial capacity. This finding highlights the importance of accessible, affordable AI solutions tailored to SME resource constraints.

Integration and Complexity Risks (Secondary Challenges)

Integration complexity (27.1%) and inadequate infrastructure (26.3%) received lower ratings than expected, suggesting that improving AI accessibility and integration capabilities may be reducing technical barriers. These finding challenges deficit-based narratives that position technical complexity as prohibitive for SMEs, indicating that contemporary AI solutions are increasingly designed for non-specialist implementation.

Return on Investment Uncertainty (Moderate Challenge)

Unclear ROI was cited by 25.4% as a challenge, with ROI assessment capability scoring relatively low ($M = 3.41$, $SD = 1.22$). This indicates difficulty quantifying AI value propositions, potentially inhibiting investment justification processes, particularly in organizations requiring formal business case approval for technology investments.

5.3.3.Benefits-Risk trade-off Analysis

The finding that perceived benefits outweigh risks ($M = 3.89$, $SD = 0.96$) is substantiated by high adoption likelihood (81.4%). However, the moderate standard deviation indicates variability in this assessment across organizations. Analysis revealed that this trade-off assessment is influenced by multiple organizational characteristics:

By Organization Size

Smaller organizations (1-50 employees) demonstrated more positive benefits-risks assessments. Mid-sized organizations (51-100 employees) exhibited greater risk concern, consistent with higher

perceived barriers. Larger organizations (101-250 employees) showed balanced perspectives, suggesting more sophisticated risk-benefit analysis capabilities developed through experience with complex technology implementations.

By Revenue Level

Higher-revenue organizations reported more favourable benefits-risks ratios. Lower-revenue organizations (< R5M) expressed greater concern about implementation costs and ROI uncertainty. Mid-revenue organizations (R26-50M) exhibited the most cautious evaluations, reflecting resource competition dynamics during growth phases.

By Operational Maturity

More established organizations (> 10 years) demonstrated more balanced, analytical assessments, suggesting that experience enhances evaluation sophistication. Newer organizations (< 5 years) showed both extremes: either highly optimistic or highly risk-averse perspectives, potentially reflecting limited experience with major technology implementations.

5.3.4. Resource Requirement Perceptions

Adequate financial resources scored moderately ($M = 3.24$, $SD = 1.32$), with significant variation indicating diverse financial positions. The positive correlation with revenue ($r = 0.41$) confirms financial capacity's role in resource perception. However, even high-revenue organizations identified financial constraints, suggesting that AI implementation costs are substantial relative to available budgets across all organizational scales.

Internal expertise received lower ratings ($M = 3.14$, $SD = 1.28$), though technology partner availability provides partial mitigation ($M = 3.65$, $SD = 1.19$). The demand for AI platform access (55.1%) indicates recognition that external resources can supplement internal capabilities. This finding suggests that ecosystem approaches emphasizing partnerships and external expertise may effectively address internal capability constraints.

While not explicitly measured quantitatively, qualitative responses revealed concerns about implementation timelines interfering with ongoing business operations, management attention required for AI initiatives diverting focus from core business activities, employee time for training and adaptation, and the extended timeframe for realizing AI benefits. These temporal considerations represent often-overlooked barriers that may delay or derail AI initiatives even when technical and financial resources are adequate.

5.3.5. Decision-Making Approaches

Thematic analysis of qualitative responses revealed three primary decision-making frameworks employed by SMEs:

1. Incremental Experimentation Approach (Predominant - ~55%)

This approach involves initiating limited-scope AI pilots, expanding based on demonstrated value, minimizing initial resource commitment and risk exposure. Organizations characterized this approach with phrases such as "testing the waters," "proof of concept," and "pilot project." This risk-mitigation strategy dominates, suggesting that most SMEs prefer evaluation and learning before substantial commitment.

2. Strategic Investment Approach (~30%)

This approach involves comprehensive AI strategy development, significant initial resource allocation, and long-term transformation perspective. More common among larger, higher-revenue organizations, this approach is characterized by terms like "strategic initiative," "digital transformation roadmap," and "competitive positioning." Organizations employing this approach typically possess greater financial capacity and established change management capabilities.

3. Reactive Adoption Approach (~15%)

This approach is characterized by adoption driven by competitive pressure or client requirements, limited strategic planning, and focus on immediate operational needs. More common among smaller, resource-constrained organizations, this approach is evidenced by phrases like "need to keep up," "client expectations," and "market demands." While potentially ensuring rapid adoption, this approach may result in suboptimal implementations lacking strategic alignment.

6. Recommendation

This section presents evidence-based recommendations to help SMEs in Gauteng effectively adopt AI technologies. The recommendations are organized across three strategic levels: organizational interventions, ecosystem enablers, and policy frameworks, forming an integrated roadmap that addresses resource constraints facing SMEs in South Africa.

6.1. Organisational-Level Recommendations

Establish a Phased AI Implementation Framework

Given that 55% of SMEs prefer incremental approaches whilst 25.4% express ROI uncertainty, organizations should implement a structured three-phase framework. Phase one involves conducting a comprehensive readiness assessment over three months, evaluating technological compatibility, organizational capacity, and environmental factors using the TOE framework. Phase two focuses on pilot implementation over six months, targeting operational efficiency improvements identified by 85.6% of respondents as the primary benefit. Suitable pilots include customer service automation, invoice processing, or predictive inventory management. Phase three involves scaled implementation over nine months, expanding successful applications whilst incorporating lessons learned.

1. Develop Comprehensive Training Programmes

With 54.2% citing technical expertise gaps as a primary barrier and 77.1% requesting training support, SMEs should implement three-tier capability development. Leadership requires AI literacy covering fundamentals, strategic implications, ethical considerations, and vendor evaluation, addressing moderate management knowledge levels (M=3.58). Organizations should upskill one to two internal specialists to build essential internal capability. All employees need general AI awareness training covering basic concepts, data quality practices, and system collaboration, addressing resistance concerns cited by 30.5% of respondents.

2. Implement Data Governance and Privacy Frameworks

With 57.6% citing data privacy as the most frequent challenge, SMEs must establish comprehensive governance encompassing data management protocols, privacy-by-design implementation, and security infrastructure. Organizations should develop clear policies aligned with POPIA requirements, implement data classification systems, and establish quality standards

for AI datasets. Privacy integration requires data minimization principles, anonymization techniques, and transparent consent management.

11.2. Ecosystem-Level Recommendations

1. Develop Strategic Technology Partnerships

The research revealed moderate internal expertise ($M=3.14$) but strong partner availability ($M=3.65$), with 44.1% identifying consulting services as critical needs. SMEs should cultivate partnerships with AI vendors offering cloud-based, modular solutions with flexible pricing; system integration consultants specializing in SME implementations; and peer learning networks through industry associations and academic collaborations. Organizations should allocate 15-25% of AI investment for partnership development, conduct thorough due diligence, establish clear contractual arrangements, and build internal capability to manage partnerships effectively rather than creating dependency.

2. Leverage Government Support Programmes

With inadequate government support rated lowest ($M=2.69$) whilst 60.2% requested financial incentives, SMEs should actively engage with existing programmes including Department of Science and Innovation funding, Industrial Development Corporation schemes, and SEDA services. Organizations should pursue sector-specific initiatives such as telecommunications operator enterprise development programmes. Beyond accessing support, SMEs should participate in industry associations advocating for improved policies, contribute to regulatory consultations, and share implementation experiences informing policy development.

11.3. Policy and systematic Recommendations

1. Advocate for Regulatory Clarity

Unclear regulations emerged as the highest barrier ($M=3.25$), with 29.7% identifying uncertainty as a top challenge. Whilst individual SMEs cannot independently resolve policy gaps, collective advocacy influences regulatory environments. Organizations should participate in business forums developing policy positions, contribute SME perspectives to consultations ensuring policies reflect small business realities, and support self-regulatory frameworks. SMEs should respond to government consultations, participate in regulatory sandboxes where available, and share experiences informing development. Implementation requires allocating time for policy engagement, coordinating with peers to amplify voices, maintaining constructive regulator relationships, and documenting compliance challenges providing concrete evidence for advocacy.

2. Promote SME-Appropriate AI Solutions

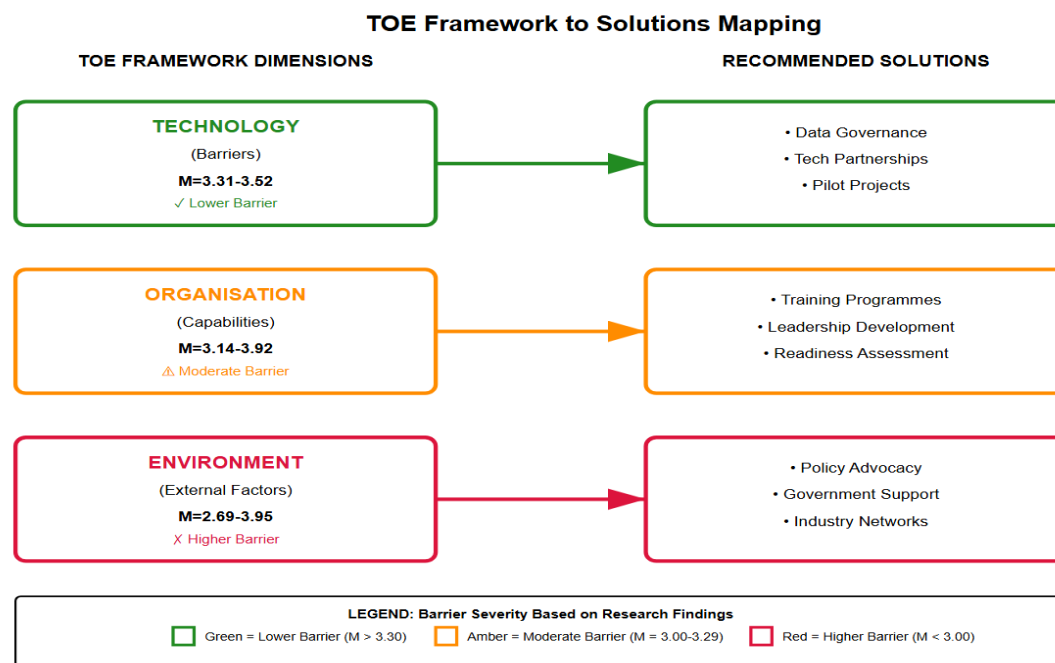
With 55.1% requesting improved platform access and 32.2% seeking cost reduction, SMEs must address supply-side gaps. Current solutions designed for enterprise markets feature misaligned pricing, complexity, and support models. Organizations should clearly articulate requirements to vendors through forums and direct engagement, specifying needs for affordable modular solutions, intuitive interfaces, flexible deployment options, and comprehensive support. SMEs should engage with developers seeking pilot users, participate in beta programmes providing refinement feedback, and leverage pilots for reduced-cost access.

The preceding recommendations establish a pragmatic implementation framework for small and medium enterprises (SMEs) in Gauteng to effectively manage AI adoption barriers and leverage associated opportunities (Dwivedi et al., 2021). Achieving successful integration necessitates a synchronized strategy across internal organizational, external ecosystem, and governmental policy dimensions, with the

acknowledgement that each SME must contextualize and tailor these guidelines according to its unique operational environment and resource capacity (Klein & Todesco, 2021).

SCHEMATIC REPRESENTATION OF THE RECOMMENDATIONS AS ADOPTED TO THE TOE FRAMEWORK

Figure 1 TOE Framework to solutions Mapping



(Author, 2025)

Figure 2 presents a strategic roadmap that guides SMEs in prioritizing AI adoption efforts based on barrier severity. The traffic light system indicates urgency: red requires immediate action, amber needs sustained investment, and green allows incremental progress.

7. Conclusion

This research examined AI and ML adoption factors among Gauteng SMEs using integrated TOE and TAM frameworks (Tornatzky & Fleischer, 1990; Davis, 1989). A quantitative methodology collected survey data from 118 SMEs across diverse sectors and sizes, achieving 92.2% response rate with rigorous validation ensuring reliability and credibility. The findings reveal significant yet surmountable challenges. Regulatory uncertainty requires clearer policy guidance and industry self-regulation, while financial barriers necessitate phased adoption strategies, government incentives, and affordable cloud-based tools. Technical expertise gaps demand targeted training, strategic partnerships, and ecosystem collaboration. These interlinked barriers require coordinated rather than isolated interventions. Despite challenges, 81.4% of SMEs intend adopting AI within two years, indicating strong awareness. The primary challenge is effective implementation through capability development, leadership engagement, and institutional support. Strategic implications include leadership communicating clear AI visions managing workforce concerns and emphasizing human augmentation. Policy frameworks must provide regulatory clarity, accessible

financing, and skills development. Vendors should design affordable, modular, user-friendly solutions aligned with SME contexts, unlocking emerging market opportunities.

Dedication

Thank you to the Great Lord Jehovah for providing the chance to research the impact of digital transformation on SMEs' adoption of AI in Gauteng, South Africa. I dedicate this work to my family, which includes my wife Precious Mosuwe, my siblings, nieces, nephews, and children Neeno' Leano Rantsoko, Booba' Lesedi, Masego, Odirile, and Omolemo. I also thank my in-laws for always asking how I'm doing, especially the future Dr. Shilela Nkadimeng, Amanda, and Mxolisi Msomi; I appreciate your presence. To my late father (Lonka, Sello Joseph Mosuwe) and my mothers, Sophie and Annah Mosuwe. I adore you all; you are the foundation of strength amid life's challenges and triumphs.

Limitations

Whilst the research provides valuable insights, several restrictions point to future directions research. The cross-sectional design records acceptance intentions and perceptions at one specific moment, which restricts the capacity to evaluate the actual outcomes of implementation. Longitudinal research tracking SMEs through the acceptance journey would provide richer understanding of implementation challenges, success factors, and outcomes. The sample, whilst robust and diverse, concentrated geographically in Gauteng's major urban centres (Johannesburg, Pretoria, Centurion-Midrand corridor), potentially limiting generalisability to SMEs in peripheral areas or other provinces.

Future Research Directions

First, longitudinal implementation research is required to trace the post-acceptance journey of SMEs, providing empirical evidence on the determinants of successful deployment, patterns of project failure, and the tangible realization of financial and operational returns (Fenech et al., 2019). Second, evaluative policy research is needed to systematically assess the efficacy of governmental and institutional support programs, measuring their direct impact on acceptance rates and business outcomes to enable evidence-based policy iteration (Nambisan et al., 2019). Finally, a vital stream of socio-ethical impact research must investigate the consequences of AI integration on employment dynamics, skill-based workforce restructuring, and the evolution of organizational culture within the SME context, thereby addressing the profound human and societal implications of technological transformation (Brynjolfsson & McAfee, 2014).

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