



Artificial intelligence adoption and business performance among small and medium enterprises in Tanzania

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ABSTRACT

Artificial intelligence (AI) is increasingly applied in business operations, yet empirical evidence on its adoption and performance implications among small and medium enterprises (SMEs) in Tanzania remains limited. This study assessed the level of AI adoption and examined its relationship with business performance among Tanzanian SMEs. The study was anchored in the Technology–Organisation–Environment (TOE) framework and Resource-Based View (RBV). A quantitative cross-sectional survey design was employed. Data were collected using a structured, self-administered questionnaire from 320 SME owners and managers in Dar es Salaam, Arusha, Mwanza and Dodoma. AI adoption and business performance were measured using five-item reflective constructs on a five-point Likert scale. Data were analysed using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4. Results revealed a relatively high level of AI adoption ($M = 3.45$, $SD = 0.82$). AI adoption had a positive and statistically significant relationship with business performance ($\beta = 0.533$, $p < 0.001$), explaining 28.4% of its variance. The findings support the RBV perspective that AI can function as a valuable technological resource. SMEs should integrate AI into relevant operations while strengthening employee skills and data practices, while policymakers should improve training, digital infrastructure and affordable AI access.

Keywords: Artificial Intelligence Adoption; Business Performance; PLS-SEM; Small and Medium Enterprises; Tanzania.

I. INTRODUCTION

Small and medium enterprises (SMEs) play an active part in job creation, revenue earning and economic development. The nature of flexibility in the structure of these firms enables them to meet local market requirements and serve those segments which might not have been taken care of by big businesses (Nor, 2024). However, this all depends upon the capability of such firms to perform well in terms of business performance. Business performance refers to the extent to which a firm accomplishes financial and non-financial objectives, including profitability, sales growth, productivity, customer satisfaction and competitive position (Kellerton, 2023). Due to various reasons (including lack of financial, technical and human capital), such firms find it difficult to maintain this level of performance (Banerjee, 2023).

The expansion of the digital economy has encouraged SMEs to reconsider traditional business practices. The study conducted in Tanzania shows that there has been an increase in the usage of ICTs in SMEs in Tanzania. As per the findings of Msuya et al. (2017), the use of ICTs in communication and marketing in SMEs in Tanzania was evident, with some SMEs linking the use of ICTs to competitiveness. Nonetheless, the evidence is related to the use of ICTs that include computers and the internet. The modern business environment involves the use of technologies that are able to learn from the data, automate activities and make decisions (Benard, 2021; Utonga et al., 2026). Consequently, the strategic question is no longer limited to whether SMEs use digital technologies, but whether they can effectively adopt artificial intelligence to improve their performance.

Adoption of Artificial intelligence (AI) refers to the deliberate use of the AI technology systems in routine tasks and decisions made by organisations (Albanese, 2024). For SMEs, this can include chatbots, predictive analysis, recommendation system, automated marketing tools, demand-forecasting system and AI-driven financial or inventory management system (Dewi, 2026). AI adoption should be distinguished from general awareness or occasional personal use of consumer applications such as ChatGPT. Adoption of AI involves application of AI technology within business processes to solve the problems faced either at the operational or marketing level. According to Kamruzzaman et al. (2025), the use of AI technology in SMEs was mostly done in customer services, marketing and operations. Paul et al. (2023) also note that AI can aid decision-making and allocation of resources.

A valuable benefit of AI is its ability to help organisations automate routine tasks, process information quickly and support managerial decisions. (Andayani et al., 2024) observed that applying AI to supply-chain, customer-service and financial operations can reduce human error, accelerate processes and improve customer satisfaction. Kandeel et al., (2024) found that AI applications improved SME productivity and profitability by reducing time spent on administrative activities and allowing employees to concentrate on business development. Similarly, Kamruzzaman et al. (2025) reported that AI contributed to more efficient business operations, cost reduction and improved customer satisfaction. Soomro et al. (2025) further found that AI adoption enhanced not only the economic performance of SMEs but also their social and environmental performance. Collectively, these findings demonstrate that AI can improve business performance through greater operational efficiency, better customer experiences and stronger competitive responsiveness.

Nevertheless, the benefits of AI adoption are neither automatic nor uniform. Outcomes may differ according to firm size, industry and resource capacity (Hizarci et al., 2024). SMEs commonly encounter high implementation costs, inadequate technical expertise and AI-system complexity (Musa et al., 2025). Other barriers include limited digital readiness, insufficient employee skills, low awareness and organisational resistance (Mustafa et al., 2025). Data quality, leadership commitment, user training and integration with existing workflows also influence implementation outcomes (Kamruzzaman et al., 2025). Therefore, an SME may acquire an AI application without obtaining substantial performance improvements, particularly when adoption is limited or poorly integrated into its operations.

These challenges are particularly having more relevance to developing countries, where the SME sector faces significant constraints regarding resource and infrastructural issues. Although international literature has shown a positive link between AI adoption and SMEs' performance, local studies in Tanzania remain scanty. The existing studies have paid less attention to AI technologies and concentrated on ICT implementation (Msuya et al., 2017). According to Luoga (2026), the use of predictive analytics and machine learning improved service quality and some aspects of supply chain efficiency at a brewing company in Tanzania. However, the benefits were constrained by organisational resistance, weak data governance and infrastructural barriers. Moreover, the study's single-case focus on a large brewery company limits the applicability of its findings to SMEs across different sectors.

An important contextual and empirical gap therefore remains. Existing knowledge does not adequately establish whether and to what extent AI adoption is associated with the overall business performance of Tanzanian SMEs. Much of the available evidence originates outside Tanzania, while local studies concentrate on traditional ICT or specific operational functions in large firms (Hamad, 2017; Msuya et al., 2017; Mwantimwa, 2019). Some existing studies are also conceptual or review-based and provide limited firm-level evidence. Because infrastructure, employee capabilities, institutional support and resource availability differ across countries, findings from other contexts cannot be applied automatically to Tanzania.

In this study, artificial intelligence adoption and its impact on business performance of SMEs in Tanzania are investigated. In this respect, the degree of AI adoption by SMEs in Tanzania will be examined. The link between AI adoption and SME performance is another issue that will be analyzed in the current study. Two research questions guide this study: What is the level of AI adoption among SMEs in Tanzania? What is the relationship between AI adoption and SME business performance? The study contributes firm-level evidence from an under-researched developing-economy context and may assist SME managers and policymakers in designing initiatives that support productive AI utilisation.

1.1 Research Objectives

- i. To assess the level of artificial intelligence adoption among small and medium enterprises in Tanzania.
- ii. Examine the relationship between artificial intelligence adoption and business performance among small and medium enterprises in Tanzania.

II. LITERATURE REVIEW

2.1 Theoretical Review

This study is grounded in the Technology Organisation Environment (TOE) framework and the Resource-Based View (RBV) of the firm. The TOE framework explains the conditions under which organisations adopt technology, whereas the RBV explains how adopted technology can contribute to firm performance. Their integration is relevant because SMEs differ in their technological readiness, managerial support, employee capabilities and ability to embed technologies within existing business processes.

2.1.1 Technology Organisation Environment (TOE)

The TOE framework, developed by Tornatzky and Fleischer (1990), proposes that technology adoption is influenced by technological, organisational and environmental conditions. The technological context concerns attributes

such as relative advantage, compatibility, complexity and cost. SMEs are more likely to adopt AI applications when their benefits are observable and the applications are compatible with existing systems. Conversely, uncertainty about business value, limited data quality and technical complexity may discourage adoption. Musa et al. (2025) identify implementation costs, specialised skill requirements and system complexity as important constraints affecting AI adoption among SMEs.

The organisational context includes the internal resources and attributes that enable firms to adopt and use technology. These include top-management support, employee competence, financial capacity, digital readiness and organisational culture. Mustafa et al. (2025) identify digital readiness and employee digital skills as critical conditions for AI adoption among SMEs. Similarly, Soomro et al., (2025) report that top-management support, employee capability and perceived relative advantage are among the strongest predictors of AI adoption. These factors are important because adoption involves more than acquiring an AI application; it requires aligning the technology with business processes, training employees and establishing appropriate data-management practices.

The environmental context includes competitive pressure, customer expectations, government support, technology vendors and digital infrastructure. Competition and changing customer behaviour may encourage SMEs to adopt AI, whereas weak infrastructure and limited external technical support may restrict adoption. Luoga (2026) found that infrastructural barriers and weak data governance constrained the benefits of AI in a Tanzanian brewery company. The TOE framework therefore provides contextual support for understanding why the level of AI adoption may differ among Tanzanian SMEs. However, its conditions are not tested as separate predictors in this study.

2.1.2 Resource-Based View (RBV)

The RBV provides the principal theoretical explanation of the relationship between AI adoption and business performance. According to Barney (1991), differences in firm performance arise from the resources and capabilities controlled and deployed by individual firms. Resources capable of producing sustained competitive advantage should be valuable, rare, difficult to imitate and not easily substitutable. AI represents a technological resource that enables firms to process information, automate routine activities, forecast demand, personalise customer interactions and improve managerial decisions. These functions may create value by reducing costs, increasing productivity and enabling firms to respond more rapidly to market changes.

Nevertheless, access to AI alone may not provide a lasting advantage because many AI applications are commercially available to competing firms. From the RBV perspective, performance benefits arise from how AI is combined with firm-specific resources, including employee knowledge, managerial commitment, proprietary data and established business processes. Kamruzzaman et al. (2025) show that clear problem definition, leadership commitment, data quality, workflow integration and user training influence successful AI implementation. Therefore, AI becomes strategically valuable when it is embedded within organisational routines and directed towards identifiable business problems. The TOE framework and RBV consequently provide complementary explanations of AI adoption and its performance implications. TOE explains how contextual conditions may influence the extent to which SMEs adopt AI, while RBV explains how adopted AI can contribute to performance when combined with firm-specific resources. Accordingly, SMEs that progress from limited experimentation to integrating AI within recurring business processes are expected to obtain greater performance benefits.

2.2 Empirical Review

Empirical Review and Hypothesis Development The empirical evidence available generally suggests that there exists a positive relationship between AI adoption and SME performance. Andayani et al. (2024) found that SMEs using AI-based automation achieved improvements in supply-chain activities, customer service and financial operations. AI use was also associated with reduced errors, faster decision-making and improved customer satisfaction. Similarly, Kandeel et al. (2024) found that AI applications enhanced SME productivity and profitability by automating administrative activities and allowing employees to devote more attention to business development.

Kamruzzaman et al. (2025) provide broader evidence from SMEs operating across different sectors. Their findings show that AI applications were used mainly in customer service, marketing and operations and that implementation positively influenced business performance. Reported outcomes included improvements in operational efficiency, customer satisfaction and cost reduction. The study further demonstrated that a problem-driven implementation approach produced better outcomes than adopting AI merely in response to technological trends or competitive pressure. This suggests that performance depends on purposeful organisational use rather than the simple availability of AI tools.

Evidence also connects AI adoption with broader performance dimensions. Soomro et al. (2025) found that AI adoption enhanced the economic, social and environmental performance of SMEs, particularly through operational efficiency, cost reduction and social value creation. Paul et al., (2023) similarly observed that AI can improve SME competitiveness by supporting decision-making, resource allocation, innovation and customer engagement. However,

Hizarcı et al. (2024) emphasise that AI outcomes vary according to industry, firm size and resource capacity. Therefore, positive performance outcomes cannot be assumed to occur uniformly across SMEs. Within Tanzania, empirical evidence directly connecting AI adoption with overall SME performance remains limited. Msuya et al. (2017) found that Tanzanian SMEs increasingly used conventional ICTs for communication and marketing and that some firms associated ICT use with improved competitiveness. However, the study did not examine AI-enabled applications. Luoga (2026) found that predictive analytics and machine learning improved service quality and selected supply-chain outcomes in a Tanzanian brewery company, but organisational resistance, weak data governance and infrastructural barriers limited these benefits. Moreover, the single-case focus on a large company restricts the applicability of the findings to SMEs.

The reviewed literature therefore reveals limited quantitative evidence from Tanzania concerning the relationship between the level of AI integration and the multidimensional business performance of SMEs across different sectors. Much of the available evidence originates outside Tanzania, while local studies concentrate on conventional ICTs or specific operational functions in large firms. Because technological infrastructure, digital capabilities and institutional support differ across countries, findings from other contexts cannot be applied automatically to Tanzanian SMEs. On the basis of the RBV, high levels of AI integration are expected to enhance operational efficiency through automation and reduced error, enhance financial performance through cost savings and productivity improvements and enhance market responsiveness through enhanced client engagement and decision making. While international studies generally report positive results, this relationship requires empirical testing in the setting of SMEs in Tanzania. Thus, the following hypothesis is proposed as follows:

H1: There is a positive and significant relationship between the level of artificial intelligence adoption and the business performance of small and medium enterprises in Tanzania

III. METHODOLOGY

3.1 Research Design and Study Area

The study employed a quantitative, cross-sectional survey design to examine the relationship between artificial intelligence adoption and business performance among small and medium enterprises (SMEs). Data were collected in June 2026 from SMEs operating in Dar es Salaam, Arusha, Mwanza and Dodoma. These regions were purposively selected as major commercial and administrative centres with substantial business activity. Therefore, the findings primarily represent SMEs operating in the selected regions.

3.2 Population and Sampling

The estimated population of small and medium enterprises in Tanzania is approximately 100,000, comprising about 83,000 small enterprises and 17,000 medium enterprises (TICGL, 2025). The target respondents were SME owners and managers because they are directly involved in technological decisions, business operations and performance assessment. The Business Registrations and Licensing Agency database provided the operational sampling frame for registered SMEs in the four selected regions.

A two-stage sampling procedure was applied. First, Dar es Salaam, Arusha, Mwanza and Dodoma were purposively selected. Second, eligible SMEs within these regions were selected through simple random sampling. Each eligible SME was assigned a unique identification number, and computer-generated random numbers were used to select the participating businesses. One owner or manager was approached from each selected SME to avoid multiple responses from the same business.

A total of 420 questionnaires were distributed, of which 350 were returned, representing a return rate of 83.3%. Following data screening, 30 incomplete or otherwise unsuitable questionnaires were excluded, leaving 320 usable responses and a usable response rate of 76.2%. The final sample of 320 responses was considered adequate for partial least squares structural equation modelling (PLS-SEM). PLS-SEM is suitable for examining relationships between latent constructs and is appropriate for studies emphasising prediction and explained variance. The sample size also substantially exceeded the minimum requirement for a model containing one predictor of the endogenous construct (Hair et al., 2022).

3.3 Instrument and Measurement

Data were collected using a structured, self-administered questionnaire comprising closed-ended questions. The first section collected respondent and business characteristics. The second measured artificial intelligence adoption, while the third measured business performance.

Artificial intelligence adoption was measured using five items coded AIA1–AIA5. The items assessed the regular use of AI-enabled applications, automation of routine activities, analysis of customer and market information,

use of AI-generated information in managerial decision-making, and integration of AI applications into recurring business processes. Business performance was measured using five items coded BP1–BP5, covering perceived sales growth, profitability, productivity, customer satisfaction and retention, and overall business performance during the preceding two years. The complete measurement items are presented in Appendix A. The measurement items were developed from the theoretical definitions of artificial intelligence adoption and business performance and informed by the reviewed empirical literature. The items were adapted to reflect the operational context of Tanzanian SMEs.

All items were measured on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Higher scores indicated greater AI adoption and stronger business performance. Both variables were specified as reflective latent constructs. The measurement properties of the constructs were assessed through the PLS-SEM measurement-model evaluation before examining the structural relationship. This assessment included indicator reliability, internal-consistency reliability, convergent validity and discriminant validity.

3.4 Data Preparation and Analysis

The returned questionnaires were checked for completeness, coded and entered into Stata for data cleaning and preliminary analysis. The data were examined for missing values, coding errors, outliers and distributional properties. Frequencies, percentages, means and standard deviations were used to summarise respondent characteristics, business characteristics and AI-adoption levels. Partial least squares structural equation modelling (PLS-SEM) was conducted using SmartPLS 4. PLS-SEM was selected because the study sought to examine the predictive relationship between artificial intelligence adoption and business performance while estimating latent constructs measured using multiple indicators. The analysis followed two stages: assessment of the measurement model and assessment of the structural model.

For the reflective measurement model, indicator reliability was assessed using outer loadings. Loadings of at least 0.708 were considered satisfactory. Internal-consistency reliability was evaluated using Cronbach's alpha, composite reliability and ρ_A , with values between 0.70 and 0.95 considered acceptable. Convergent validity was assessed using average variance extracted, for which values of at least 0.50 were considered satisfactory. Discriminant validity was evaluated using the heterotrait–monotrait ratio of correlations, with values below 0.85 indicating adequate discriminant validity.

After establishing the reliability and validity of the measurement model, the structural model was assessed using collinearity statistics, the standardised path coefficient, coefficient of determination, effect size and predictive relevance. Inner variance inflation factor values below 3 indicated the absence of critical collinearity. The significance of the structural relationship was evaluated through bootstrapping using 5,000 subsamples, a two-tailed test and a 5% significance level. The results were reported using the standardised path coefficient, bootstrap standard error, t-value, p-value and 95% bias-corrected confidence interval. The model's explanatory power was evaluated using R^2 , while the contribution of AI adoption to business performance was assessed using the f^2 effect size. Predictive relevance was evaluated using Q^2 , with values above zero indicating predictive relevance. Because data for the predictor and outcome constructs were obtained from the same respondents using a single questionnaire, Harman's single-factor test was conducted as a preliminary assessment of common-method bias. A first-factor variance below 50% was interpreted as indicating that no single factor dominated the measurement items.

3.5 Validity and Reliability

The questionnaire was reviewed by 5 experts in business management, information technology and research methodology to assess the relevance, clarity and contextual suitability of its measurement items. It was subsequently pretested with 10 SME owners and managers who were excluded from the final study. Their feedback was used to refine the wording and clarity of the questionnaire.

The reliability of the measurement model was assessed using Cronbach's alpha, ρ_A and composite reliability. Cronbach's alpha coefficients for artificial intelligence adoption and business performance were 0.902 and 0.832, respectively, exceeding the adopted threshold of 0.70. Convergent validity was confirmed through average variance extracted values of 0.720 and 0.597, both exceeding the minimum threshold of 0.50. Discriminant validity was established using the heterotrait–monotrait ratio of correlations, which produced a value of 0.612, below the 0.85 threshold. These results collectively confirmed that the measurement model demonstrated satisfactory reliability and validity for structural equation modelling.

3.6 Ethical Considerations

The study followed established ethical principles for low-risk social science research. Permission to collect data and access the sampling frame was obtained from the relevant authorities. Participants received information explaining the study's purpose, voluntary participation, right to withdraw and intended academic use of the findings. Informed consent was obtained before questionnaire completion. No names, registration numbers or other identifying information

were collected. Responses were treated confidentially, stored securely and reported in aggregate form to prevent the identification of individual respondents or businesses. No incentives were offered, and participation did not affect respondents' relationships with regulatory or government institutions.

IV. FINDINGS & DISCUSSION

4.1 Respondent and Business Characteristics

Table 1 presents the characteristics of the 320 respondents and their businesses.

Table 1

Respondent and business characteristics

Characteristic	Category	Frequency	Percentage
Gender	Male	186	58.1
	Female	134	41.9
Respondent position	Owner	128	40.0
	Manager	192	60.0
Business experience	Less than 1 year	32	10.0
	1–3 years	64	20.0
	4–6 years	96	30.0
	7 years or more	128	40.0
Region	Dar es Salaam	128	40.0
	Arusha	96	30.0
	Mwanza	64	20.0
	Dodoma	32	10.0
Business size	Small enterprise	128	40.0
	Medium enterprise	192	60.0
Business sector	Manufacturing	64	20.0
	Trade	96	30.0
	Services	80	25.0
	Agriculture/agribusiness	32	10.0
	Construction	16	5.0
	Transport/logistics	32	10.0
Business age	Less than 3 years	32	10.0
	3–5 years	32	10.0
	6–10 years	128	40.0
	More than 10 years	128	40.0
AI-adoption status	Uses AI	256	80
	Does not use AI	64	20
Duration of AI use among adopters	Less than 1 year	96	37.5
	1–2 years	128	50.0
	3 years or more	32	12.5
	Total AI adopters	256	100.0

Note: Percentages for AI-use duration are based on the 256 SMEs that reported using AI.

Source: Authors' analysis of survey data (2026).

The sample consisted of 60% managers and 40% owners, suggesting that the information was gathered from people who are directly involved in the operation and decision-making of the business. The majority of the respondents had good knowledge of their businesses since 70% of the respondents had worked in their respective enterprises for a minimum of four years. The sample consisted of 58.1% male respondents and 41.9% female respondents. The four selected study regions were included in the sample. The largest proportion of respondents was from Dar es Salaam (40%), followed by Arusha (30%), Mwanza (20%) and Dodoma (10%). The sample consisted of firms from different sectors with the highest representation being in the trade sector (30%) followed by services (25%) and manufacturing (20%). Most of the businesses were already well established with 80% of them operating for at least six years. Data were collected from 60% medium enterprises and 40% small enterprises. Regarding AI-adoption status, 256 SMEs (80%) reported using AI-enabled applications, while 64 SMEs (20%) reported no current AI use. Among the 256 AI adopters, 37.5% had used AI for less than one year, 50% for one to two years and 12.5% for at least three years. Thus, 87.5% of the adopters had used AI for no more than two years, indicating that AI adoption among the surveyed SMEs was widespread but remained relatively recent.

4.2 Descriptive Statistics

Table 2 presents the descriptive statistics for the study constructs.

Table 2

Descriptive statistics

Construct	N	Mean	Standard deviation	Minimum	Maximum
Artificial intelligence adoption	320	3.45	0.82	1.20	5.00
Business performance	320	3.81	0.74	1.40	5.00

Source: Authors' analysis of survey data (2026).

The mean score of 3.45 (SD = 0.82) indicates a relatively high level of AI adoption among the surveyed SMEs. This finding is supported by the adoption-status data, which show that 80% of the SMEs reported using AI-enabled applications. However, AI adoption appears to be relatively recent, as 87.5% of adopters had used AI for no more than two years. This suggests that although AI use is becoming widespread among the surveyed SMEs, many firms may still be transitioning from initial adoption towards deeper integration into recurring business processes. The finding is consistent with Kamruzzaman et al. (2025), who observed increasing use of AI applications among SMEs, particularly in customer service, marketing and operations. It also complements Mustafa et al. (2025), who emphasised digital readiness and employee digital skills as important conditions for AI adoption among SMEs. In the Tanzanian context, the finding extends earlier evidence from Msuya et al. (2017), which demonstrated increasing use of conventional ICTs among SMEs but did not specifically examine AI-enabled applications. The relatively high but recent adoption observed in the present study therefore suggests a progression from conventional digital technology use towards AI-enabled business applications among the surveyed Tanzanian SMEs.

4.3 Measurement-Model Assessment

The reflective measurement model was evaluated using outer loadings, Cronbach's alpha, rho_A, composite reliability and average variance extracted. The results are presented in Table 3.

Table 3

Reflective measurement-model assessment

Construct	Indicator	Outer loading	Cronbach's alpha	rho_A	Composite reliability	AVE
AI adoption	AIA1	0.825	0.902	0.904	0.928	0.720
	AIA2	0.771				
	AIA3	0.881				
	AIA4	0.881				
	AIA5	0.878				
Business performance	BP1	0.778	0.832	0.840	0.881	0.597
	BP2	0.786				
	BP3	0.768				
	BP4	0.718				
	BP5	0.810				

Source: Authors' analysis using SmartPLS 4 (2026).

All outer loadings exceeded 0.708 and ranged from 0.718 to 0.881, indicating satisfactory indicator reliability. Cronbach's alpha, rho_A and composite reliability were evaluated to establish internal-consistency reliability. The Cronbach's alpha, rho_A and composite reliability values exceeded 0.70 and remained below 0.95, demonstrating satisfactory internal-consistency reliability without indicating indicator redundancy. The AVE values of 0.720 for artificial intelligence adoption and 0.597 for business performance exceeded the minimum threshold of 0.50, confirming convergent validity. Discriminant validity was assessed using the Fornell–Larcker criterion and heterotrait–monotrait ratio. The square roots of the AVE were 0.848 for AI adoption and 0.773 for business performance. Both values exceeded the inter-construct correlation of 0.533. The HTMT value was 0.612, with a 95% confidence interval ranging from 0.542 to 0.678. Because the HTMT value was below 0.85 and its confidence interval did not include 1.00, discriminant validity was established.

Harman's single-factor test showed that the first unrotated factor accounted for 37.8% of the total variance. Because this value was below 50%, no single factor dominated the measurement items. Although this test cannot

conclusively eliminate common-method bias, it provided preliminary evidence that such bias was unlikely to explain most of the observed relationships.

4.4 Structural-Model Assessment

Following confirmation of the reliability and validity of the measurement model, the structural model was assessed. The inner VIF value for the relationship between artificial intelligence adoption and business performance was 1. This value was below the recommended threshold of 3, indicating that collinearity did not affect the structural-model estimates. The R^2 value for business performance was 0.284, indicating that artificial intelligence adoption explained 28.4% of the variance in business performance. The adjusted R^2 value was 0.282. The Q^2 value of 0.152 was greater than zero, demonstrating that the model had predictive relevance for business performance.

Table 4

Structural-model assessment

Endogenous construct	Inner VIF	R^2	Adjusted R^2	Q^2
Business performance	1.000	0.284	0.282	0.152

Source: Authors' analysis using SmartPLS 4 (2026).

4.5 Relationship Between AI Adoption and Business Performance

The estimated structural model, including standardised factor loadings, the structural-path coefficient and the explained variance in business performance, is presented in Figure 2.

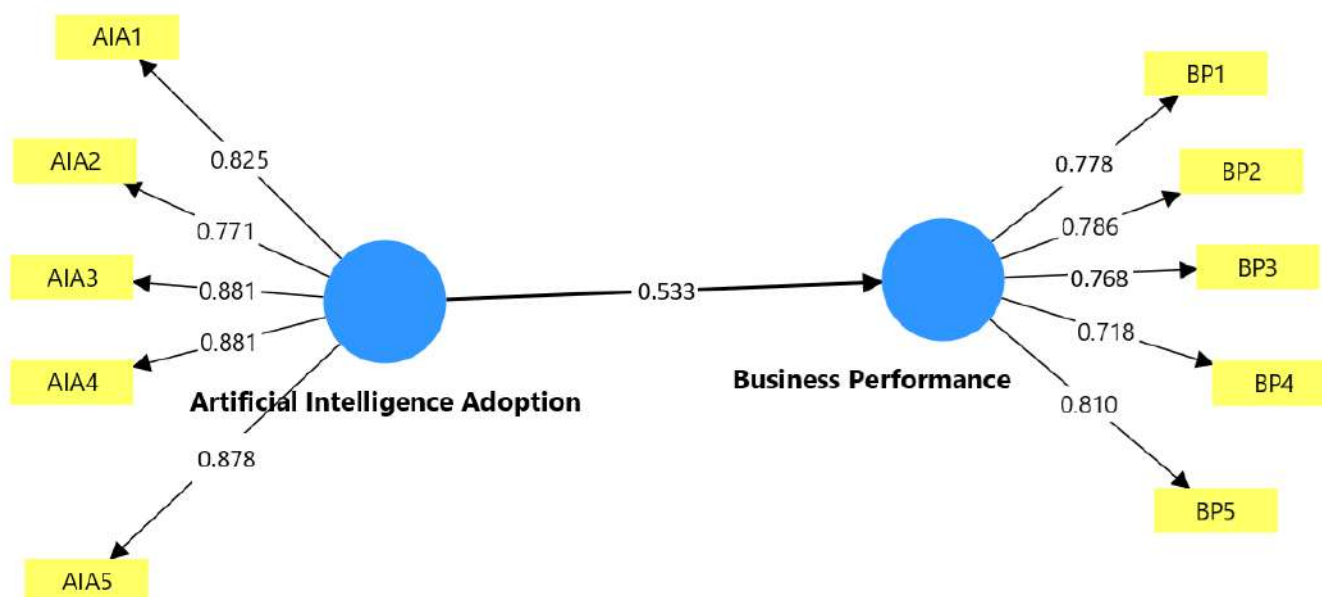


Figure 2

Estimated structural model of AI adoption and business performance

Note: Values beside the indicators are standardised factor loadings; the value on the structural path is the standardised coefficient. $R^2=0.284$ for business performance.

Source: Authors' analysis using SmartPLS 4 (2026).

Table 5 presents the estimated relationship between AI adoption and business performance.

Table 5*Structural relationship and hypothesis decision*

Relationship	β	Bootstrap SE	t-value	p-value	95% confidence interval	f^2	Decision
AI adoption → Business performance	0.533	0.074	7.203	<0.001	[0.388, 0.676]	0.397	Supported

Source: Authors' analysis using SmartPLS 4 (2026).

The PLS-SEM results showed that artificial intelligence adoption had a positive and statistically significant relationship with business performance ($\beta = 0.533$, $t = 7.203$, $p < 0.001$). The 95% bias-corrected confidence interval [0.388, 0.676] did not include zero. Therefore, H1 was supported. Artificial intelligence adoption explained 28.4% of the variance in business performance ($R^2 = 0.284$). The f^2 value of 0.397 indicated a large contribution of AI adoption to the explained variance in business performance. The positive relationship suggests that SMEs achieving higher levels of AI integration tend to report stronger financial and non-financial performance. AI may improve performance by automating routine activities, reducing errors, supporting faster decisions and enabling firms to respond more effectively to customer and market information. This explanation is consistent with Andayani et al. (2024), who associated AI-powered automation with improved operational efficiency, faster decision-making and customer satisfaction. It also agrees with Kandeel et al. (2024), who found that AI applications enhanced SME productivity and profitability by allowing employees to focus on business-development activities.

The findings are also consistent with Kamruzzaman et al. (2025), who reported that AI implementation improved operational efficiency, customer satisfaction and cost reduction among SMEs. Similarly, Soomro et al., (2025) found that AI adoption enhanced several dimensions of SME performance. The result extends this evidence to the Tanzanian context, where earlier research mainly examined conventional ICT adoption. Msuya et al. (2017) associated ICT use among Tanzanian SMEs with improved communication, marketing and competitiveness, but did not consider more advanced AI-enabled applications.

From the RBV perspective, the findings support the argument that AI can operate as a valuable technological resource when integrated into organisational processes. Nevertheless, AI applications are widely accessible and may not be rare or difficult to imitate by themselves. Their performance value is therefore likely to depend on how SMEs combine them with managerial commitment, employee knowledge, business data and established workflows. This interpretation is consistent with Kamruzzaman et al. (2025), who identified leadership commitment, data quality, workflow integration and user training as important conditions for successful AI implementation. The unexplained variance of 71.6% indicates that business performance is also influenced by factors beyond AI adoption, such as financing, managerial capability, market conditions, employee competence and institutional support. Moreover, the cross-sectional design establishes association rather than definitive causality. The result should therefore be interpreted as evidence that higher AI adoption is associated with stronger performance, rather than proof that AI adoption alone causes performance improvement.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

This study examined the level of artificial intelligence adoption and its relationship with business performance among SMEs operating in Dar es Salaam, Arusha, Mwanza and Dodoma. In relation to the first objective, the findings revealed a relatively high level of AI adoption, with an overall mean score of 3.45. Although 80% of the surveyed SMEs reported using AI-enabled applications, adoption remained relatively recent, as 87.5% of adopters had used AI for no more than two years. This indicates that AI use is becoming increasingly common among the surveyed SMEs, although many businesses may still be progressing towards deeper integration of AI into recurring business processes.

Regarding the second objective, AI adoption had a positive and statistically significant relationship with business performance ($\beta = 0.533$, $p < 0.001$). AI adoption explained 28.4% of the variance in business performance ($R^2 = 0.284$), while the effect size ($f^2 = 0.397$) indicated a substantial contribution to the explained variance. Thus, SMEs reporting higher levels of AI adoption also tended to report stronger sales growth, profitability, productivity, customer satisfaction and retention, and overall business performance. However, because the study employed a cross-sectional design, these findings demonstrate an association rather than establish a definitive causal relationship. Overall, the study concludes that AI adoption is an increasingly relevant technological resource for Tanzanian SMEs and that greater integration of AI into business activities is associated with stronger business performance. Nevertheless, AI adoption alone does not account for all differences in SME performance, as 71.6% of the variance remains unexplained by the model. The performance value associated with AI should therefore be understood within the broader organisational context in which the technology is applied.



5.2 Recommendations

Based on the findings, SMEs should progressively integrate AI-enabled applications into recurring business processes, particularly in areas where they can support operational efficiency, customer service, marketing, information analysis and managerial decision-making. Since AI adoption is still relatively recent among most surveyed SMEs, owners and managers should strengthen employee skills, data quality and the effective integration of AI tools into existing workflows rather than focusing only on acquiring the technology. Policymakers and SME-support institutions should facilitate productive AI adoption through practical AI training, improved digital infrastructure and affordable access to appropriate AI technologies. Such support should particularly help resource-constrained SMEs develop the capabilities required to translate AI adoption into improved business performance.

Declaration of Interest

The author declares that he does not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A: Measurement Items

Respondents indicated their level of agreement with each statement on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

Construct	Code	Measurement statement
Artificial intelligence adoption	AIA1	Our business regularly uses AI-enabled applications in its operations.
	AIA2	Our business uses AI to automate routine activities.
	AIA3	Our business uses AI to analyse customer, sales or market information.
	AIA4	AI-generated information is used to support managerial decision-making in our business.
	AIA5	AI-enabled applications are integrated into our recurring business processes.
Business performance	BP1	Our business has experienced satisfactory sales growth during the past two years.
	BP2	The profitability of our business has improved during the past two years.
	BP3	The productivity of our business has improved during the past two years.
	BP4	Our business has improved its customer satisfaction and retention during the past two years.
	BP5	The overall performance of our business has improved during the past two years.