

Research Article

From AI Readiness to Knowledge Advantage: Explaining SME Performance through a TAM-TOE-KBV Framework

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Abstract: This study examines the determinants of the innovation readiness of SMEs, as well as the effect of AI on knowledge creation and SME performance in Ghana. The study builds on the extended Technology Acceptance Model, the Technology-Organisation-Environment framework and the Knowledge-Based View, and examines the relationship between technological, organisational and environmental factors and AI readiness, and as well as between AI readiness and knowledge-based competitive outcomes. A cross-sectional quantitative design was used. The secondary data analyzed were harmonized to create a confirmatory analytical dataset of 412 SME observations from Ghana derived from the World Bank Enterprise Survey 2023, SME Reports, Ghana eTrade Readiness Assessment, and the Bank of Ghana FinTech Sector Report Q1 2025. The findings show that the quality of digital infrastructure, financial resources availability and top management's commitment are the most important factors for the readiness to engage in AI innovation. Organisation absorptive capacity has a significant mediation effect on the relationship between knowledge creation and AI readiness; and between firm performance and AI readiness. But it's also significantly influenced by the regulatory landscape, and that can vary from firm to firm depending on the size. This study adds to the digital innovation and SME performance literature by introducing TAM, TOE and KBV in the context of sub-Saharan Africa. It contextualises the potential contribution of the National AI Strategy 2025-2035 in creating enabling conditions for AI readiness, knowledge building and performance improvement of SMEs in Ghana.

Keywords: artificial intelligence; innovation readiness; knowledge creation; SMEs; TAM-TOE; digital transformation; firm performance

1. Introduction

The advent of artificial intelligence (AI) is changing the landscape of competition, knowledge production and innovation in industries globally (McAfee & Brynjolfsson, 2017). AI presents both a challenge and an opportunity for development in sub-Saharan Africa, where many businesses are not formally registered, digital infrastructure is not robust, access to finance is uneven, and they lack technical capacity. Ghana is one such interesting country to study the issue. We are experiencing a rapidly evolving digital economy, a strong fintech industry, and a growing ecosystem of small and medium enterprises that use digital tools to create, market, communicate with customers, and perform financial transactions. The Ghanaian case is apt in the light of the recent developments.

Mobile money transaction value increased to GH¢3.3 trillion and mobile money accounts rose to 26.7 million in 2024, up 73.7% from 2023 (Bank of Ghana, 2025a). It's a digital financial penetration that can facilitate widespread technology adoption by companies. Simultaneously, a 2025 UNDP Human Development Survey found that over 70% of respondents in Ghana were hopeful that AI would enhance productivity in the workplace, especially in the agriculture, public service, and education sectors (&&&). The Ghana National AI Strategy 2025 to 2035 is another indicator of a more formal national policy agenda, rather than a few informal experiments with AI tools (Ministry of Communication, Digital Technology and Innovations, 2026). The strategy emphasizes the need for Ghana to become AI ready as a key pillar of its digital transformation efforts, with a goal of having GH¢200 billion worth of AI-related foreign direct investment and private-sector investment by 2035.

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This policy move is a good thing, but there is limited literature related to the adoption of AI by African small and medium-sized enterprises (SMEs). Although research on the subject of AI innovation in emerging economies has garnered much attention in the Asia context, the same cannot be said for the Sub-Saharan Africa context, as there are fewer scholars with backgrounds in the area represented in existing empirical studies on AI innovation (Abrokwah-Larbi & Awuku-Larbi, 2024; Badghish & Soomro, 2024). Also, theories in literature are very unorganized. The technology acceptance model (TAM) (Davis, 1989) addresses technology usage, emphasising perceived usefulness and perceived ease of use; while the technology organization environment (TOE) model (Tornatzky & Fleischer, 1990) looks at the resources, conditions and pressures of technology and the organisation. However, these frameworks are insufficient to reflect the relationship between AI readiness, knowledge creation and business performance.

However, this is addressed by the knowledge-based view (KBV), which views knowledge as a strategic resource that helps companies create value, learn, and compete (Grant, 1996). In light of this, the integration of TAM, TOE, and KBV provides a more solid theoretical foundation for examining Ghanaian SMEs' preparation for AI and the extent to which this readiness is operationalised to achieve innovation outcomes. This study examines the factors that affect the innovation readiness of SMEs in Ghana and how innovation readiness affects knowledge creation and company performance in the AI era. Specifically, the study focuses on the technological, organizational and environmental factors that affect AI readiness, assesses whether there is a mediational effect between absorptive capacity and knowledge creation and performance, and provides concrete suggestions for managers, policy makers and development stakeholders.

The paper is more than just about being prepared for AI. It will illustrate concrete conditions for SMEs to act, including access to reliable digital infrastructure; digital tools and services at affordable prices; top management commitment; employees' digital skills; availability of financial resources; digital data governance capacity; and regulatory clarity and support mechanisms provided by the sector. The study tests the proposed relationships with partial least squares structural equation modelling (PLS-SEM) using secondary data integrated from the World Bank Enterprise Survey (2024), SME competitiveness report (International Trade Centre, 2017), and the United Nations Conference on Trade and Development. (2023), Ghana eTrade Readiness Assessment (United Nations Conference on Trade and Development, 2023), and fintech sector data (Bank of Ghana, 2025a). Hopefully, the contribution will be threefold.

This paper is theoretically grounded on the TAM and TOE and links the AI readiness with the outcomes of KBFs via the KBV mechanism. Empirically, it has evidence-based content on readiness to innovate with AI in SMEs in sub-Saharan Africa, where there are significant resource limitations and a growing opportunity in the digital domain. At the practical level, it marks key steps to further increase the AI readiness of SMEs in Ghana: increase the digital infrastructure, expand SMEs access to AI financing, further develop SME managers and employees AI literacy, develop regulatory sandboxes for the responsible use of AI, strengthen data protection and cyber security compliance, and link SME innovation programmes to the National AI Strategy 2025 to 2035.

Specifically, the study aims to examine how AI innovation readiness contributes to knowledge creation and firm performance among Ghanaian small and medium enterprises (SMEs). Accordingly, the study is guided by the following research objectives; to examine the effect of digital infrastructure quality on AI innovation readiness; To determine the effect of perceived usefulness of AI on AI innovation readiness; To assess the effect of top management commitment on AI innovation readiness; To examine the effect of AI innovation readiness influence knowledge creation; And finally, to determine the effect AI innovation readiness on the performance of Ghanaian SMEs.

2. Literature Review

2.1. *AI Adoption and Innovation in Developing Economies*

Since 2020, there has been a substantial growth in research on AI use in developing economies, with a high proportion of the evidence being available in South and Southeast Asian markets, as explored by Rana et al. (2024). Digital innovation scholarship has been

more focused in Sub-Saharan Africa on mobile money, fintech adoption and digital financial inclusion (Abor & Quartey, 2023). Conversely, the concept of AI capability, innovation readiness and knowledge creation of SMEs is not well theorized nor developed in practice. Based upon the available evidence, however, technologies can boost productivity, operational efficiency, market reach, responsiveness to customers and financial performance of SMEs when they have the capacity to operationalise the technologies (Badghish & Soomro, 2024; Fu et al., 2025; Wamba-Taguimdje et al., 2020).

This has sparked the concept of innovation readiness, which helps explain why some businesses can fully leverage technology for success while others are merely experimenting. This is because the notion of innovation readiness has become a key one: some companies gain benefits from AI; others are simply playing around. In this study, the concept of AI-driven innovation readiness is defined as a company's readiness across the technological, human capital, financial, strategic, and organisational dimensions to effectively implement AI tools and transform them into innovation (Dey & Ghose, 2025). More than an adoption drop-off is needed. It requires the right digital infrastructure, trained employees, leadership buy-in, investments, data, a sense of cyber-literacy, and a roadmap to leveraging AI for core business processes.

2.2. TAM and TOE Framework

One of the most influential models explaining technology adoption is the TAM (Davis, 1989). The model shows that perceived usefulness and perceived ease of use affect users' attitudes towards a technology, which in turn affect their behavioural intention and actual use of that technology. Perceived usefulness is users' confidence that the technology will enhance their effectiveness in completing their job, and perceived ease of use is users' confidence that the technology is user-friendly, easy to use and manage, and requires little effort.

This idea of Venkatesh et al. (2003) was further extended with the unified theory of acceptance and use of technology (UTAUT), a theory that included social influence, facilitating conditions, and performance expectations in the study of technology adoption. In the AI space, Fabio Ibrahim et al. (2025) also point out that attitudes towards AI exist between perceived usefulness and intention to use AI, highlighting the need to help people adopt AI by making them understand the value, usefulness, and relevance of the technology to them. Tornatzky and Fleischer's (1990) gives a more comprehensive explanation of technology adoption through TOE, by identifying three sets of contextual determinants: technological, organisational, and environmental contexts.

The merger of the two would provide a more comprehensive analytical foundation to analyse Ghanaian SMEs' readiness for AI-driven innovations. The TAM is about managers and employees' perception of usefulness and usability of AI tools, while TOE is about the conditions in the organisation and the environment which facilitate or obstruct AI adoption. In the study of Al-Fryan et al. (2026), integration of TAM-TOE in the context of AI-driven innovation for SMEs in emerging markets, TAM-TOE enables multi-level analysis of the dynamics of acceptance and readiness conditions of the individual firms. In the case of Ghana, this integrated framework is especially relevant as it captures the various factors that can affect the adoption of AI by SMEs, such as managerial perception, the digital infrastructure, financial resources, employee capabilities, competitive pressure, and the regulatory frameworks and national policy environments.

2.3. KBV and AI-Driven Knowledge Creation

In Grant's KBV (1996), the firm is viewed as an institution with the ability to create, combine, protect and apply knowledge to out-compete others. This is a knowledge perspective which sees knowledge as the resource to an organization. It is a resource that plays a key role in the strategic process of learning, innovation and sustaining performance edge for firms. The socialization-externalization-combination-internalization (SECI) model by Nonaka and Takeuchi (1995) also provides insight into the process of knowledge creation as a result of interactions between tacit and explicit knowledge. Firms transform individual experiences, discursive knowledge, formalised knowledge and the routine of the organisation to usable knowledge for innovation through socialisation, externalisation, combination and internalisation.

The application of AI technologies also amplifies these processes by making the

information flow and processing faster, more extensive and more analytical, and turning it into decisions. Machine learning, natural language processing, predictive analytics, generative AI, and these technologies can help businesses find market trends, automate knowledge retrieval, improve their predictive modeling, support product innovation, and increase their customer intelligence (Fu et al., 2025). But an AI-driven advantage does not always translate to a knowledge-based advantage.

This mechanism is especially relevant to Ghanaian SMEs as there are sector, SME type and size, and digital maturity differences in knowledge management capacities. Absorptive capacity is applied as a construct in this research, which posits that it serves as a theoretical connection between absorptive capacity and knowledge-based outcomes of innovation. It gives an insight into how the same company can yield varying results using the same AI tools.

2.4. Theoretical Framework and Hypothesis Development

This paper proposes a structural model based on the TAM-TOE-KBV framework to clarify the role of the technological, organisational and environmental factors on the innovation readiness of individuals and how this innovation readiness impacts knowledge-based outcomes. Five major construct domains are included in the model. The first domain concerns technological conditions and includes the quality of digital infrastructure and the perceived usefulness of AI. These factors reflect SMEs' level of digital maturity when it comes to infrastructure, and the benefits they recognize for AI to improve business processes, decision-making and innovation.

The second domain refers to organisational conditions and comprises the top management commitment, absorptive capacity and financial resource availability. They are internal resources needed to facilitate the implementation of AI, such as management support, the capacity to identify and utilize external knowledge, and the resources available for digital investments. The third domain is the external, situational factors, Regulatory Environment and Competitive Pressure, that can support or obstruct AI readiness of SMEs. The concept of AI Innovation Readiness is included as a mediating concept in the model. It's a testament to the company's eagerness to put AI tools to use and adopt them. Another important feature of the model is that it establishes knowledge creation and firm performance as the two main constructs in the model. In this context, it is expected that AI readiness will drive technological, organisational and environmental enablers, leading to a higher amount of knowledge production, innovation capability and business performance. The conceptual model proposed is shown in figure 1.

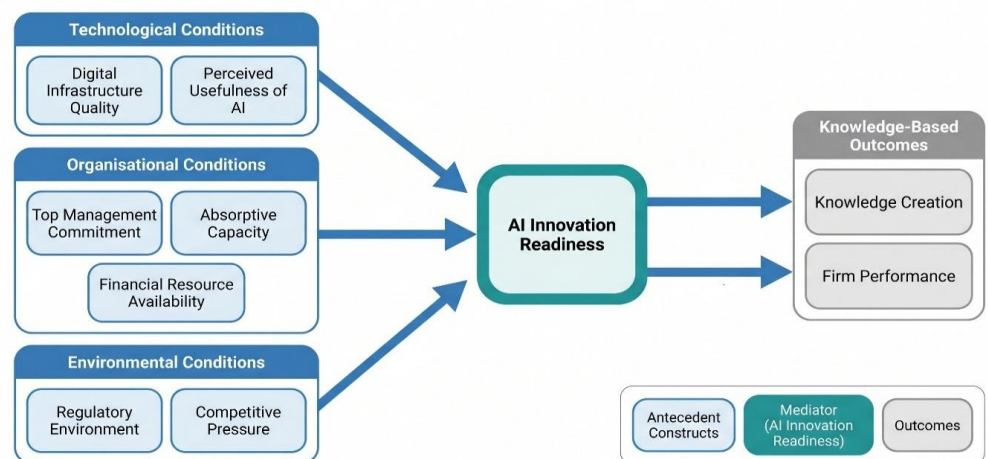


Figure 1. Integrated TAM-TOE-KBV conceptual model of AI-driven innovation readiness.

Note: DIQ = digital infrastructure quality; PU = perceived usefulness; TMC = top management commitment; AIIR = AI innovation readiness; KC = knowledge creation; FP = firm performance.

AI adoption by SMEs requires the basic condition of the quality of digital infrastructure. It includes the reliability of the internet, access to computing power, mobile network

reliability, cloud service availability, and the availability of digital platforms that companies can leverage for data processing with their own customers, the automation of tasks, and the use of AI tools in day-to-day operations. If the infrastructure isn't reliable, the use of AI will be limited, as companies may not have access to cloud-based applications, maintain digital records, analyse data, or have real-time interaction with suppliers or customers. This is a significant issue in Ghana.

The previous studies highlighted by Baabdullah et al. (2021) identified the quality of digital infrastructure as a key driver for the adoption and readiness of technology in similar developing economy situations. As a result, digital infrastructure quality is expected to have a positive impact on the AI innovation readiness of Ghanaian SMEs in this study.

H1: Digital infrastructure quality is positively correlated with the AI innovation readiness of Ghanaian SMEs.

Perceived Usefulness, based on the TAM, is the degree to which SME managers believe that AI tools can help the organisation run more efficiently, make better business decisions, increase organisational productivity, and improve overall business performance. It is particularly significant in the SME sector, as owner-managers and decision-makers are likely to decide whether new technologies are adopted, funded, and integrated into the day-to-day work. The greater the managers' perception of the value of AI to help cut costs, customer interaction, market analysis, inventory management, process automation, and innovation, the more resources they are willing to allocate to preparing for AI. This construct is evidenced in Ghana.

The results of the survey in Ghana showed that over 70% of respondents were positive about AI's contribution to workplace productivity, indicating a positive perception of AI's role in organisational performance (United Nations Conference on Trade and Development, 2023). Positive sentiment is crucial, as it can influence managerial receptiveness to adopting AI tools, developing digital skills, and restructuring business processes and workflows around AI applications. Previous research also confirms the significance of perceived usefulness when it comes to AI adoption. Fabio Ibrahim et al. (2025) find that perceived usefulness continues to predict behavioural intention to use AI, especially if users think that AI will bring clear benefits to their work. Therefore, it is hypothesized that the perceived usefulness will have a positive impact on AI innovation readiness of Ghanaian SMEs.

H2: Perceived usefulness of AI is positively associated with AI innovation readiness among Ghanaian SMEs.

Top management commitment is relevant, as part of organisational conditions for AI innovation readiness among SMEs. It's about the effectiveness of senior leaders and owner-managers to provide strategic leadership, resource allocation, promote the benefits of AI, and support employee learning and resistance to technology-driven change. In small and medium-sized enterprises, where decision-making authority may be concentrated in the hands of a few, managerial buy-in can be a critical factor in the successful implementation of AI. The importance of top management commitment to the adoption of AI is well established in the literature.

Managerial support becomes crucial in the process of technology adoption because of its influence on investment decision, organisational culture, employee acceptance and implementation continuity as mentioned by Chatterjee et al. (2020). This is important for AI adoption, as it often requires several changes to data practices, workflows, employee roles, customer engagement, and decision-making processes. This becomes critical in the case of SMEs, where resources are limited. The adoption of AI is competing with pressing operational constraints such as working capital, inventory, customer acquisition, and cost control. But if management is not ready, it may not be the SME's confidence, discipline, or resources that will take them from awareness to readiness. Therefore, it is expected that the top management commitment has a positive impact on the Ghanaian SMEs' AI innovation readiness.

H3: Top management commitment is positively associated with AI innovation readiness among Ghanaian SMEs.

KBV proposes that a competitive advantage does not result from technology, but from technological creation processes, integration and application processes. In this way, AI tools can only be strategically useful when companies are willing to use them to derive insights,

enhance learning, optimise decisions and reinforce the organization's processes. In this study, AI innovation readiness is then the key intervening variable that transforms technological, organisational and environmental factors into knowledge creation and firm performance. This mediation logic is significant because digital infrastructure, managerial support and financial resources, absorptive capacity, regulatory clarity and competitive pressure do not necessarily lead to improved performance.

Such conditions must first be interpreted as AI readiness, that is, the ability of the firm to put AI tools into practice, map them to business needs, understand and apply the results of AI, and integrate the results into business functions and decision-making. Only then can AI play an impactful role in knowledge creation and performance enhancement. This also aligns with the dynamic capabilities theory (Dey & Ghose, 2025), which focuses on firms' capacity to sense opportunities, seize them by mobilising resources, and reconfigure internal processes to adapt to technological change. The AI Innovation Readiness does that in this study. It provides insight into how companies transition from having adoption-enabling conditions to knowledge-based, performance-based outcomes.

H4: AI innovation readiness mediates the relationship between TAM-TOE antecedent factors and knowledge creation.

H5: AI Innovation readiness mediates the relationship between TAM-TOE antecedent factors and firm performance.

3. Materials and Methods

3.1. Research Philosophy and Design

The research philosophy used in this study is positivist because the relationships among the constructs are pre-specified by theory and measured. The positivistic approach assumes that social and organizational phenomena are observable, quantifiable and amenable to empirical systematic procedures. Based on the hypothetico-deductive tradition, the study starts with theory-based assumptions, and the assumptions are converted into hypotheses, which are subsequently tested using statistical analysis (Bryman, 2016). This philosophical approach is appropriate for the study because it aims to explain why some SMEs in Ghana are better prepared to advance the innovation of AI than others and how it affects their knowledge creation and firm performance.

The cross-sectional quantitative research design is used. This design enables the study to investigate relationships between underlying constructs over a specific time frame and to determine the strength, direction, and significance of the proposed structural relationships. It is also appropriate for PLS-SEM analyses because it examines multiple predictors, mediation processes, and outcome variables within a single conceptual model. The data used in the study is secondary data obtained from authoritative sources of institutions and harmonized into composite analytical data. This should be done when country- or firm-specific reliable indicators exist from existing databases, sector reports and policy assessments.

More practically, the use of secondary data is also described as justifiable in the research setting in this research area of Ghana, where primary data collection, due to their size, may be limited by cost, access and time. The data set is used with care, however, to ensure the conceptual consistency between theoretical constructs and their empirical indicators. All of the variables are assigned to the TAM-TOE-KBV framework and pretreated for confirmatory analysis. This design thus offers a defensible empirical basis for testing the influence of technological, organisational and environmental conditions on AI readiness and its implications for knowledge and performance outcomes.

3.2. Data Sources and Secondary Data Integration Strategy

A secondary data integration approach that leverages four institutional data sources covering key indicators of AI innovation readiness for Ghanaian SMEs is adopted to examine the innovation readiness of SMEs in Ghana. Four institutional data sources are used in this study, employing a secondary data integration approach to examine innovation readiness among Ghanaian SMEs using the provided indicators. The first comes from the Enterprise Survey 2009-2013-2019-2024 (World Bank, 2024), which has information on business operations, technology use, managerial practices, financial constraints, and competitive conditions and performance-related outcomes at the firm level.

This source is the primary source for the SME level observations, which are used to operationalise the indicators for digital infrastructure quality, top management commitment, financial resource availability, competitive pressure, AI innovation readiness and firm performance. The second one is the SME Competitiveness Report that is available to give information at sector and enterprise levels on areas of SME digital access, infrastructure, enterprise competitiveness, innovation activity and capacity in knowledge management (International Trade Center, 2017). The indicators are used to complement the firm-level indicators and to enhance the assessment of digital infrastructure quality, absorptive capacity and knowledge creation.

The third source is the Ghana eTrade Readiness Assessment (United Nations Conference on Trade and Development, 2023), which offers evidence on digital skills, AI awareness, perceived usefulness of AI, policy readiness and regulatory conditions. The indicators are aligned with perceived usefulness, regulatory environment and AI innovation readiness. The fourth is the FinTech Sector Report Q1 2025 (Bank of Ghana, 2025a), which offers insights into Ghana's digital financial ecosystem, fintech activity, payment infrastructure and financial-sector digitalisation. These indicators are used in association and to provide context for financial resource availability and firm performance.

Data integration has been carried out in a systematic three-step approach. First, variables from each source were checked and were only included if they were conceptually similar to the theoretical constructs of the TAM-TOE-KBV model. Second, harmonisation of the firm-level and contextual indicators followed, where possible, through common classification fields including sector, firm size and region. Third, variables were standardised to make them comparable across the sources and missing observations were handled with multiple imputations if the rate of missingness was less than 15%. The last analytical data obtained were 412 observations of the SME, which were prepared for confirmatory analysis with PLS-SEM.

3.3. Construct Operationalisation and Measurement

Based on the requirement of PLS-SEM in modelling unobservable theoretical constructs with multiple indicators (Hair et al., 2019), all constructs in the model were operationalised as reflective latent variables. This specification is suitable because the indicators are evidence of their respective constructs rather than components of those constructs. For instance, digital infrastructure quality, top management commitment, absorptive capacity, and AI innovation readiness are conceptualised as underlying conditions of the organisation, as evidenced by related measurable indicators. Indicators for each construct were identified from harmonised secondary data and aligned with the theoretical constructs within the TAM-TOE-KBV framework.

The indicators were selected for their conceptual relevance, empirical availability, and consistency with previous technology adoption and innovation readiness studies. When necessary, source variables were standardized to be compatible across scales and data sources. The definitions of the constructs and the number of indicators and source variables measured for each construct in the model are shown in Table 1.

Table 1. Construct operationalisation summary.

Construct	Definition and indicators	No. items	Source
Digital infrastructure quality (DIQ)	Internet reliability, mobile bandwidth, computing access, platform availability	4	Fridkin et al., 2024
Perceived usefulness (PU)	Belief AI improves productivity, efficiency, decision quality, market responsiveness	4	United Nations Conference on Trade and Development, 2023; Fridkin et al., 2024
Top management commitment (TMC)	Leadership support, resource dedication, strategic alignment, innovation culture	5	Fridkin et al., 2024; Lu et al., 2026
AI innovation readiness (AIIR)	Organisational preparedness across tech, human capital, financial, and strategic	5	United Nations Conference on Trade and Development, 2023

dimensions			
Knowledge creation (KC)	New product/service	4	Lu et al., 2026
	knowledge generation, process knowledge improvement, market knowledge accumulation		
Firm performance (FP)	Revenue growth, productivity improvement, customer acquisition, profitability relative to sector peers	4	Ho et al., 2022

3.4. PLS-SEM as Analytical Method

The choice of the analytical technique was made because of the requirements of the model, its structure and the nature of the data for this research. PLS-SEM was chosen as the analytical method to suit this research model, its structure and data. Firstly, the study's objectives aim to explain variance in endogenous constructs, such as AI innovation readiness, knowledge creation and firm performance, making PLS-SEM suitable for prediction-oriented research (Hair et al., 2019; Margalina et al., 2026).

Second, the method can estimate relatively complex structural models with multiple predictors, mediators and latent constructs without the strict multivariate normality assumptions. This is crucial, as the study is based on a harmonised secondary data set drawn from multiple sources. Third, PLS-SEM can be applied in a moderate sample size and thus can be used for the final analytical data of 412 observations of the SMEs. Fourth, SmartPLS 4.0 offers strict protocols to estimate measurement and structural models as well as bootstrapping with 5,000 resamples to test the significance of path coefficients, indirect effects and mediation relationships (Margalina et al., 2026).

The analysis was conducted in two stages using PLS-SEM, as suggested by Hair et al. (2019). The first stage was the measurement model, which was used to determine the reliability and validity of the latent constructs. The reliability of indicators was checked by outer loadings, and values of 0.70 or higher were deemed acceptable. Cronbach's alpha and composite reliability were used to assess internal consistency, with a minimum threshold of 0.70. Convergent validity was tested by average variance extracted; the indicators of each construct explained more than 0.50 (more than half) variance. Discriminant validity was evaluated according to the Heterotrait-Monotrait ratio, with a ratio lower than 0.85 considered as good discriminant validity.

The second stage was the evaluation of the structural model. This included the analysis of path coefficients, t-statistics and p-values as well as the coefficients of determination, predictive relevance and effect sizes. The fit of the model was evaluated by the coefficient of determination, and the predictive relevance was checked with the Q^2 value > 0 . The relative contribution of each exogenous construct was investigated using f^2 statistics. Bootstrapped indirect paths with percentile confidence intervals were used to test for mediation effects. This analytical approach will give us a sound basis to analyse the influence of technological, organisational and environmental factors on AI innovation readiness and the influence of AI Innovation Readiness on knowledge creation and firm performance for Ghanaian SMEs.

3.5. Ethical Considerations and Data Governance

The secondary data was publicly available and anonymous data from well-known institutional sources were used in this study. No primary data was gathered from human subjects, no one was approached, recruited or observed for the research. For this reason, institutional review board approval was not required for the study. However, the study has been carried out with respect to the ethical standards of the scientific community, such as transparency, responsible use of data, protection of confidentiality and accurate attribution of sources.

All datasets used in the study were used in aggregated or anonymised form and no personally identifiable information was collected, processed or reported. The data handling process was based on the principles of purpose limitation and data minimisation, that is, only the variables directly related to the study objectives were extracted, harmonised and analysed.

The data were used for academic study only and were not manipulated in any way that could vitiate the integrity of the original data. All the institutional data providers are fully acknowledged, and all the sources are mentioned in the manuscript for transparency, verification and replication. The harmonised analytical data set and variable coding procedure could be shared by the corresponding author on reasonable request, provided with the access conditions and use restrictions of the data providers.

3.6. Sample Description

The harmonised analytical data included 412 observations from SMEs in Ghana. SMEs as companies with a workforce of 5-249 employees (Li et al., 2021). By using this definition, the study was able to focus on the enterprises that are sufficiently formalised and able to interact with digital technologies, but at the same time are subject to the financial, managerial, and infrastructural constraints which are common to small and medium-sized enterprises. The sample, thus, gives an adequate empirical context to consider the innovation readiness of AI in an SME setting in Ghana.

Table 2 shows the distribution of the sample by the major firm-level characteristics such as firm size, sector, region, ownership structure and years of operation. The reason for this is that not all SMEs will be ready for AI to the same degree. Larger companies can have greater financial and technical ability, and companies operating in digitally oriented industries can be more vulnerable to competition and technology-driven innovation. Likewise, disparities in digital infrastructure and market access can shape the readiness and capability of SMEs to prepare for and embrace tools powered by AI.

Table 2. Sample Demographic Profile.

Characteristic	Category	Frequency (n)	Percentage (%)
Firm size	Micro (5-9 employees)	98	23.8
	Small (10-49 employees)	187	45.4
	Medium (50-249 employees)	127	30.8
Sector	Trade and commerce	118	28.6
	Manufacturing	89	21.6
	Financial and fintech services	74	18.0
	Agriculture and agribusiness	62	15.0
	ICT and digital services	69	16.7
	Greater Accra region	198	48.1
Location	Ashanti region	94	22.8
	Other regions	120	29.1
Digital adoption level	High (uses ≥ 3 digital tools)	156	37.9
	Moderate (1–2 digital tools)	194	47.1
	Low (no digital tools)	62	15.1

4. Results

4.1. Measurement Model Assessment

Table 3 shows the results of the measurement model for the study constructs that were measured as latent variables. The results show that all the retained indicators had outer loadings greater than the recommended value of 0.70, suggesting that the indicators were reliable. These imply that the indicators measured the theoretical concept well with high factor loadings and that they were meaningful. Internal consistency reliability also was obtained. The internal reliability of the instruments used, as measured by composite reliability values, were between 0.81 and 0.93, and Cronbach's alpha values ranged between 0.76 and 0.91. Both sets of values were above the minimum recommended cut-off of 0.70; the internal consistency of the indicators for each of the constructs was appropriate for continued structural analyses.

The average variance extracted values (0.59 to 0.92) were higher than the acceptable minimum of 0.50 thus confirming the convergent validity. This indicates that over 50% of the variance in the indicators of each of these constructs was accounted for. Heterotrait-

Monotrait ratio criterion was used to test for discriminant validity. All HTMTs were lower than the conservative value of 0.85, indicating that the constructs were empirically distinct and separate from each other. The overall results of the measurement model show that reliability, convergent validity and discriminant validity are satisfactory, which serves as a foundation for assessing the structural model.

Table 3. Measurement model result.

Construct	Outer Loadings Range	Cronbach's α	CR	AVE	Max HTMT
DIQ	0.72-0.84	0.79	0.85	0.58	0.72
PU	0.74-0.88	0.82	0.87	0.62	0.68
TMC	0.71-0.89	0.85	0.89	0.61	0.74
AIIR	0.76-0.91	0.91	0.93	0.68	0.76
KC	0.74-0.87	0.83	0.88	0.64	0.73
FP	0.73-0.86	0.82	0.87	0.63	0.71

4.2. Structural Model Results

The results of the structural model are shown in table 4, which includes the path coefficients, the bootstrapped t-statistics and the significance level derived from 5,000 bootstrap resamples. The results revealed that all hypothesized relationships were statistically significant. The model was found to have a good level of explanatory power. It explained 61.4% of the variance of knowledge creation and 54.7% of the variance of firm performance. The values of R^2 shown demonstrate the model has a good explanatory power of the integrated TAM-TOE-KBV model in explaining the relationship between AI Innovation Readiness and knowledge and performance outcomes of Ghanaian SMEs.

Table 4. Structural model path coefficients (bootstrap n = 5,000).

Hypothesis / path	Relationship	β	t-stat	p-value	Result
H1	DIQ $\rightarrow$ AIIR	0.41	7.38	< 0.001	Supported
H2	PU $\rightarrow$ AIIR	0.26	4.91	< 0.001	Supported
H3	TMC $\rightarrow$ AIIR	0.33	6.12	< 0.001	Supported
H4	AIIR $\rightarrow$ KC	0.38	6.74	< 0.001	Supported
H5	AIIR $\rightarrow$ FP	0.29	5.18	< 0.01	Supported
AIIR mediation: AC $\rightarrow$ KC	Indirect effect	0.08	3.22	< 0.01	Mediated
R^2 (KC)	0.614	—	—	—	—
R^2 (FP)	0.547	—	—	—	—

Note: Significant at $p < 0.05$ level; size-moderated effects found. β = standardised path coefficient.

The same results were obtained for the predictive relevance where Q^2 equaled 0.39 for knowledge creation and 0.34 for firm performance. The two values are significantly greater than 0, suggesting that the structural model has sufficient predictive relevance. In general, the results support the proposed model and validate AI innovation readiness as a valid mediator between technological, organisational and environmental factors with SME knowledge creation and performance.

4.3. Mediation Analysis

Bootstrapped indirect effects were estimated for the test of H8a and H8b. The results indicate that the link between absorptive capacity and knowledge creation was fully mediated by AI innovation readiness ($\beta = 0.08$, 95% CI [0.032, 0.141], $t = 3.22$, $p < .01$). This result confirms partial mediation and suggests that absorptive capacity has an indirect effect on knowledge creation via AI readiness, in addition to its direct effect. The overall effect of absorptive capacity on knowledge creation was $\beta = 0.21$, of which the indirect effect accounted for 38.1% of the overall effect.

This indicates that a significant part of the knowledge creation value of absorptive capacity comes from the firm's willingness to put them into practice and integrate them.

Likewise, AI innovation readiness was also partially mediating the connection between top management commitment and firm performance ($\beta = 0.09$, 95% CI [0.038, 0.157], $t = 3.41$, $p < .001$). The finding suggests that managerial commitment is a partial determinant of firm performance through increasing the organisational conditions necessary for the adoption, implementation and use of AI. That is, high-level commitment is not enough. It becomes more significant as it makes the firm ready to leverage AI for operational efficiencies, decision-making, customer engagement, and innovation.

These results combined provide evidence that AI innovation readiness is an important mechanism for the transformation of organisational capabilities into knowledge and the outcomes of performance. This aligns with the KBV which states that not only does the firm need to possess enough resources, it needs to integrate, apply and transform knowledge into productive value.

4.4. Moderation Analysis: Firm Size Effects

To test the effect of firm size on the link between regulatory environment and AI innovation readiness, a post-hoc multi-group analysis was performed in SmartPLS 4.0. The results reveal that the relationship was moderated by the size of the firm. That is, medium sized companies ($\beta = 0.29$, $p < .001$) were significantly more likely to be at the AI Innovation Readiness level than were the micro enterprise companies ($\beta = 0.08$, $p = .24$). This suggests that regulatory clarity and policy support will have a more positive impact on AI readiness for firms with an adequate organisational capacity to interpret, absorb and respond to the policy signals.

This is a theoretically significant result since it indicates that the impact of the regulatory environment does not occur naturally. Regulations, national AI strategies, data protection rules and digital policy frameworks set the enabling conditions, but firms need to have the internal capacity to turn the enabling conditions into readiness. Medium-sized firms are more likely to have formal managerial structures, financial resources, digital systems and awareness of regulations, which enable them to leverage regulatory clarity. In contrast, micro-enterprises might not have human, financial and technical resources that can be used to interpret policy signals and make practical decisions about the adoption of AI.

The outcome will have implications for the implementation of Ghana's National AI Strategy. For more mature companies, a general regulatory approach may be more appropriate; however, smaller companies will need targeted support, simplified compliance guidance, affordable training, digital advisory services and sector-specific implementation tools. Otherwise, national AI policy could exacerbate the readiness disparities between large and medium-sized companies and small businesses.

5. Discussion

Among the Ghanaian SMEs, digital infrastructure quality ($\beta = 0.41$) was the most powerful predictor of AI innovation readiness, highlighting its critical role for Ghana's AI development agenda. While Ghana has impressive headline statistics such as 72.2% penetration rate of the internet and over 90% 4G coverage, these statistics do not reflect the quality, reliability and affordability of digital access to SMEs. The lack of network coverage and the use of 4G, which is currently below 60%, is a structural constraint on AI readiness. Applications using AI often need to be connected to the internet, cloud, and have storage, reliable devices, and ongoing digital interaction. In these cases, companies might know about AI, and possibly be interested in adopting it, but have difficulty getting it to be part of normal business.

The result is in line with previous studies in other similar developing economy settings in which the quality of digital infrastructure is consistently found to be a precondition for technology adoption and innovation capacity (Baabdullah et al., 2021). It further aligns with the policy rationale of other initiatives that focus on infrastructure, like the government's planned AI computing centre and the National Payment Systems Strategy 2025 to 2029 (Bank of Ghana, 2025b), which acknowledge a need for increased investment in connectivity, computing power, secure data systems, and interoperability of digital platforms to drive advanced digital transformation.

This work is theoretically extended to TAM-TOE literature, as it demonstrates that DIG

quality is not just another adoption factor in the context of resource-constrained SMEs. It establishes the real-world limit of AI readiness. While managers may see the benefits of AI and be willing to commit, lack of connectivity and limited computing access and unreliable digital systems can restrict what is feasible in their implementation. This is a crucial qualifier for the balanced assumptions typically made in TAM-TOE studies done in contexts of infrastructure-richness. While Managerial commitment and Employee capability and strategic intent can support AI readiness, it must start with the infrastructure and is not something that can be achieved without them.

Also, top management commitment ($\beta = 0.33$) was the second strongest predictor of AI innovation readiness, further supporting the notion that there is a strong link between technology adoption and leadership-based explanations (Chatterjee et al., 2020; Sang, 2024). The insights are especially valuable in Ghana's SME environment as AI adoption is frequently hindered by the presence of uneven AI literacy, technical expertise, and competing operational priorities. The involvement of owners, chief executives and senior managers is the key in such situations.

Managerial support is about providing direction and strategic support for AI adoption, legitimizing investment in AI, making resources available and communicating to employees that AI is not a side project but a part of the firm's innovation program. It also helps to lower resistance as it fosters a culture or mindset that's less fearful of technology-driven change. This outcome is consistent with the findings of United Nations Conference on Trade and Development (2023). Ghana eTrade Readiness Assessment) in Ghana, revealing a general positive sentiment towards the potential of AI for enhancing productivity at work. But a positive attitude isn't enough to be ready, though. Based on the evidence, Ghana business leaders need to translate the positive attitudes into tangible managerial implementation such as investing in the acquisition of digital tools, training employees, data systems, increasing awareness of cybersecurity, and redesigning processes.

SMEs are more likely to progress from awareness to preparedness when it comes to AI when it is supported by top management. Absorptive capacity ($\beta = 0.22$) and financial resource availability ($\beta = 0.27$) also contribute to an organisation's capacity in an important complementary way. The absorptive capacity boosts the firm's capacity to identify, absorb and utilize external knowledge, and financial resource availability will allow the firm to gain access to the tools, training, and technical support required to implement AI. Based on the mediation results, a total of 38.1% of the total effect of absorptive capacity on knowledge creation is mediated by AI innovation readiness. This is an affirmation that the ability to learn is not useful without combining with other capacities. It tends to be more productive when the companies are ready and willing to implement AI and leverage AI-driven insights into their knowledge workflows.

This discovery contributes to the KBV as it highlights that absorptive capacity is transformed into knowledge creation via AI readiness in a technologically dynamic environment. Competitive advantage will not be one of just having information or using AI tools for Ghanaian SMEs. It will come from the creation of the organisational readiness needed to move external knowledge, digital resources and insights generated by AI into new processes, better decisions and performance enhancing innovation.

One of the most theoretically meaningful study findings is the positive and significant correlation between AI innovation readiness and knowledge creation ($\beta = 0.38$). It offers empirical proof of the KBV as it provides evidence that AI brings value to the organisation not just by having the digital tools, but by evolving a readiness to embed the digital tools in learning routines, decision processes and innovation activities. In this context, AI readiness is not just a state of technological readiness but a mindset. It is an organisational capability that allows the firms to transform data, digital applications and external knowledge into new ideas, enhanced processes, customer understandings and market-relevant innovation.

The significance of this discovery is even more relevant in the Ghanaian SME environment, where fintech and digital business innovations like the interoperability of mobile money, AI-based credit scoring, digital insurance, automated customer support, and platform-based services are gaining momentum. SMEs that are more mature in terms of AI readiness will be better equipped to engage with these innovation ecosystems as it is not just about buying pre-developed AI solutions from larger companies or external providers. These

companies can leverage AI to better understand customer needs, assist in internal collaboration and communication, analyze market signals, and redesign products or services based on evolving business conditions.

Moreover, the model's explanatory power for knowledge creation ($R^2 = 0.614$) further suggests that the integrated TAM-TOE-KBV framework provides a solid theoretical foundation to understand how Knowledge Outcomes can be explained by the AI readiness of Ghanaian SMEs. This finding implies that when technological conditions, organizational capacities and environmental pressures are leveraged through AI readiness at the firm level, these factors gain value to the firm. The finding thus significantly builds on previous work in the field of AI adoption studies, as it demonstrates how readiness acts as a vehicle for the conversion of AI adoption resources into knowledge creation and, ultimately, competitive advantage.

This research is three-fold theoretically contributory in the literature of AI adoption, SME's innovation and knowledge-based competitiveness. First, it builds on the TAM-TOE model by adding the KBV, which not only clarifies the drivers behind AI adoption, but also the impact on knowledge creation and firm performance. This extension is crucial as most literature on AI adoption addresses the intent, acceptance or implementation of AI, rather than organisational outcomes which are the key to the strategic value of AI. In connecting technological, organisational and environmental factors with knowledge creation and performance, the study demonstrates that AI readiness should be embedded in a knowledge-based competitiveness process.

Second, the study proposes and tests a multidimensional mediating construct called AI innovation readiness. The study does not view readiness as a one-off binary choice but as a more complex organisational trait that entails infrastructure readiness, managerial commitment, financial capability, absorptive capacity, regulatory awareness and competitive responsiveness. The conceptualisation helps to deepen the scholarly understanding of the potential of AI for firms by highlighting the need for preparedness regarding use, interpretation and integration of AI-supported tools and processes in business routines and decision-making.

Third, the moderation by the regulatory environment to AI innovation readiness relationship by the firm size is useful boundary conditions for TAM-TOE theory. While the impact of environmental factors is generally assumed to be the same for all firms, the results suggest that the clarity of the regulation is more important for firms that have adequate organisational capacity to interpret and respond to policy signals. This contribution is especially relevant to a population of SMEs that is heterogeneous, as in emerging economies, the micro, small and medium sized firms exhibit variation in their resources, capabilities and institutional readiness.

6. Conclusions

The study developed and tested an integrated TAM-TOE-KBV model of AI innovation readiness and its implications for knowledge creation and firm performance among SMEs in Ghana. Based on 412 observations from a systematically harmonised secondary dataset, the findings identify digital infrastructure quality, top management commitment, and financial resource availability as the strongest antecedents of AI readiness. Perceived usefulness, absorptive capacity, competitive pressure, and the regulatory environment also contribute, although their effects are comparatively weaker and context-dependent.

The findings demonstrate that AI innovation readiness functions not merely as an outcome of technology adoption but as a strategic mechanism through which organisational resources and environmental conditions contribute to knowledge creation and firm performance. The model explains 61.4% of the variance in knowledge creation and 54.7% in firm performance, highlighting the importance of organisational readiness in translating AI-related capabilities into knowledge-based advantages.

These findings are particularly relevant to Ghana's evolving digital landscape and the National AI Strategy 2025-2035. However, policy ambition alone is unlikely to ensure widespread AI adoption. Persistent inequalities in infrastructure quality, access to finance, managerial capabilities, and regulatory preparedness may constrain SMEs' ability to benefit from AI. Effective implementation therefore requires alignment between national policy,

organisational readiness, and firm-level capabilities.

The findings suggest five policy priorities. First, digital policy should move beyond expanding connectivity towards ensuring reliable, affordable, and high-quality digital infrastructure, including access to cloud services, cybersecurity, and technical support. Second, AI readiness frameworks should be differentiated by firm size, with simplified assessment tools, affordable AI literacy programmes, and practical regulatory guidance for micro and small enterprises.

Third, funding mechanisms such as the National AI Fund should incorporate knowledge-readiness criteria, including existing digital capabilities, employee skills, learning capacity, and engagement with business networks. Fourth, leadership development should form part of national AI initiatives, with programmes enabling SME owners and managers to make informed strategic decisions about AI investment and responsible implementation. Fifth, government-supported AI knowledge hubs could reduce sectoral knowledge gaps by providing demonstrations, advisory services, templates, and peer-learning opportunities, particularly for less technologically advanced sectors.

For SME managers, AI readiness should be approached as an organisational transformation process rather than simply technology acquisition. Managers should assess preparedness in four key areas: digital infrastructure, employee skills, financial capacity, and knowledge-management practices. Investments in employee training, knowledge sharing, data quality, and external networking are essential for converting AI adoption into meaningful organisational knowledge and performance improvements. AI readiness should therefore be treated as a continuous learning process requiring strategic leadership, gradual implementation, effective data management, staff development, and appropriate financial planning. Partnerships with business associations, universities, innovation hubs, and technology providers can further address capability gaps. Rather than adopting AI rapidly for its own sake, SMEs should focus on applications that strengthen knowledge creation, operational efficiency, and sustainable competitiveness.

The study has two main limitations. First, its reliance on secondary institutional data restricts the measurement of constructs such as Absorptive Capacity and AI Innovation Readiness, which may require direct assessment of managerial perceptions and organisational practices. Future research should therefore collect primary data from Ghanaian SMEs through surveys, interviews, and case studies to provide more precise measurement and deeper insight into how firms adopt and use AI. Second, the cross-sectional design limits causal interpretation and does not capture changes in AI readiness over time. Longitudinal studies could follow SMEs through different stages of Ghana's National AI Strategy to assess the long-term effects of infrastructure investment, financial support, AI literacy programmes, and regulatory measures on readiness, knowledge creation, and performance. Future research could also test the TAM-TOE-KBV model comparatively in other West African economies, such as Nigeria, Senegal, and Côte d'Ivoire, to examine its applicability across different regulatory, infrastructural, and innovation environments.

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Declaration on AI Application: AI was used to check the grammatical errors and sentences and was also used to create the conceptual model.

References

- Abor, J., & Quartey, P. (2023). Technology and entrepreneurship in Ghana: The role of mobile technology. *African Journal of Business Management*, 17(3), 123-135.
- Abrokwhah-Larbi, K., & Awuku-Larbi, Y. (2024). The impact of artificial intelligence in marketing on the performance of business organizations: Evidence from SMEs in an emerging economy. *Journal of Entrepreneurship in Emerging Economies*, 16(4), 1090-1117. <https://doi.org/10.1108/JEEE-07-2022-0207>

- Baabdullah, A. M., Alalwan, A. A., Slade, E. L., Raman, R., & Khatatneh, K. F. (2021). SMEs and Artificial Intelligence (AI): Antecedents and Consequences of AI-Based B2B Practices. *Industrial Marketing Management*, 98, 255-270. <https://doi.org/10.1016/j.indmarman.2021.09.003>
- Badghish, S., & Soomro, Y. A. (2024). Artificial Intelligence Adoption by SMEs to Achieve Sustainable Business Performance: Application of Technology-Organization-Environment Framework. *Sustainability*, 16(5), 1864. <https://doi.org/10.3390/su16051864>
- Bank of Ghana. (2025a). FinTech sector report: Quarter 1, 2025. <https://www.bog.gov.gh/wp-content/uploads/2025/05/FinTech-Sector-Report-2025-Q1.pdf>
- Bank of Ghana. (2025b). National payment systems strategy 2025-2029. <https://www.bog.gov.gh/wp-content/uploads/2026/02/NATIONAL-PAYMENT-SYSTEMS-STRATEGY-2025-2029.pdf>
- Bryman, A. (2016). *Social research methods*. Oxford University Press.
- Chatterjee, S., Nguyen, B., Ghosh, S. K., Bhattacharjee, K. K., & Chaudhuri, S. (2020). Adoption of artificial intelligence integrated CRM system: An empirical study of Indian organizations. *The Bottom Line*, 33(4), 359-375. <https://doi.org/10.1108/BL-08-2020-0057>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. <https://doi.org/10.2307/249008>
- Dey, D., & Ghose, D. (2025). Integrating AI Adoption Frameworks with Digital Maturity Models: Strategic Pathways in a Rapidly Evolving Technological Landscape. *Journal of Contemporary Business Research*, 1(2), 156-170. <https://doi.org/10.1177/3049513X251387463>
- Fabio Ibrahim, F., Nils-Torge Telle, N.-T., Philipp Yorck Herzberg, P. Y., & Münscher, J. C. (2025). The construction and validation of the AI mindset scale (AIMS). *Computers in Human Behavior: Artificial Humans*, 6, 100220. <https://doi.org/10.1016/j.chbah.2025.100220>
- Fridkin, S., Greenstein, G., Cohen, A., & Damari, A. (2024). Perceived Usefulness of a Mandatory Information System. *Applied Sciences*, 14(16), 7413. <https://doi.org/10.3390/app14167413>
- Fu, Y., Ni, J., & Fang, M. (2025). The impact of artificial intelligence on digital enterprise innovation. *Journal of Strategy & Innovation*, 36(1), 200538. <https://doi.org/10.1016/j.jsinno.2025.200538>
- Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17, 109-122. <https://doi.org/10.1002/smj.4250171110>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2-24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Ho, L. T., Gan, C., Jin, S., & Le, B. (2022). Artificial Intelligence and Firm Performance: Does Machine Intelligence Shield Firms from Risks? *Journal of Risk and Financial Management*, 15(7), 302. <https://doi.org/10.3390/jrfm15070302>
- International Trade Center. (2017). SME Competitiveness in Ghana. <https://www.intracen.org/resources/publications/sme-competitiveness-in-ghana>
- Li, Z., Anaba, O. A., Ma, Z., & Li, M. (2021). Ghanaian SMEs Amidst the COVID-19 Pandemic: Evaluating the Influence of Entrepreneurial Orientation. *Sustainability*, 13(3), 1131. <https://doi.org/10.3390/su13031131>
- Lu, X., Shen, W., & Li, F. (2026). AI-HI collaboration, knowledge creation and organizational technology commercialization. *Journal of Knowledge Management*. <https://doi.org/10.1108/JKM-12-2025-1774>
- Margalina, V. M., Kreienbaum, C., Hair, J. F., Becker, J.-M., & Ringle, C. M. (2026). Multiple linear and logistic regression analysis: a SmartPLS 4 software tutorial. *Journal of Marketing Analytics*, 14, 709-726. <https://doi.org/10.1057/s41270-026-00466-2>
- McAfee, A., & Brynjolfsson, E. (2017). *Machine, Platform, Crowd: Harnessing Our Digital Future*. W.W. Norton & Company.
- Ministry of Communication, Digital Technology and Innovations. (2026). Ghana national artificial intelligence strategy 2025-2035. <https://www.africadataprotection.org/Ghana-AI-Strat.pdf>
- Nonaka, I., & Takeuchi, H. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. Oxford University Press. <https://doi.org/10.1093/oso/9780195092691.001.0001>
- Rana, M. M., Siddiquee, M. S., Sakib, M. N., & Ahamed, M. R. (2024). Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. *Heliyon*, 10(18), e37569. <https://doi.org/10.1016/j.heliyon.2024.e37569>
- Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.
- United Nations Conference on Trade and Development. (2023). Ghana eTrade Readiness Assessment. https://unctad.org/system/files/official-document/dtlecdc2023d7_en.pdf
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>
- Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, 26(7), 1893-1924. <https://doi.org/10.1108/BPMJ-10-2019-0411>
- World Bank. (2024). World Bank Enterprise Survey 2009-2013-2019-2024. <https://microdata.worldbank.org/catalog/8143>