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Structural Constraints as Moderators in the Ai–performance Relationship: Evidence from Smes in an Emerging Economy

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Abstract

Artificial intelligence (AI) adoption is increasingly recognized as a source of competitiveness for small and medium-sized enterprises (SMEs). Yet, prior research has primarily treated structural constraints such as financial scarcity, skill shortages, and institutional weaknesses as mere barriers, leaving their post-adoption impact underexplored, particularly in emerging economy contexts. This study empirically examines a relationship that has been theoretically acknowledged but rarely tested in such settings. Drawing on the Resource-Based View, Contingency Theory, and Institutional Theory, we propose a multidimensional framework explaining why AI adoption does not uniformly translate into performance gains but depends on firms' financial capacity, technical competencies, and institutional environment. Using survey data from 280 Tunisian SMEs analyzed with partial least squares structural equation modeling (PLS-SEM), results confirm that AI adoption significantly improves financial and operational performance. Financial and technical strengths amplify these effects, whereas institutional conditions exert no significant moderating influence, suggesting that firms compensate for institutional weaknesses through adaptive and informal mechanisms. By reconceptualizing structural constraints as post-adoption moderators rather than pre-adoption barriers, this study advances understanding of contextual contingencies shaping AI outcomes and provides insights for managers and policymakers in resource-limited economies.

Keywords: Artificial Intelligence (Ai), Small and Medium-sized Enterprises (Smes), Structural Constraints, Performance, Emerging Economies

Introduction

The global economy is currently experiencing a deep and multidimensional transformation, largely driven by the rapid progress of digitalization and the exponential development of artificial intelligence (AI). In sectors such as finance, healthcare, automotive, agriculture, and logistics, AI is redefining the boundaries of productivity, innovation, and competitiveness. By enabling the analysis of massive datasets and the automation of complex processes, AI has become a key driver of efficiency and strategic decision-making. However, this technological revolution, while opening new horizons for growth, also raises crucial challenges related to ethics, data security, and the future of employment (Olimov, 2025).

Despite the growing diffusion of AI technologies, their benefits are not equally distributed across contexts. In developing countries, and particularly in Africa, AI adoption and its tangible impact on firm performance remain limited by deep-rooted structural barriers (World Bank, 2022; Sdiri, 2023). Tunisia provides a revealing example of these disparities. Small and medium-sized enterprises (SMEs), which account for over 90% of businesses and nearly half of private employment (INS, 2023), face a dual challenge. On one hand, they must accelerate their digital transformation to remain competitive; on the other, they continue to struggle with restricted access to finance, insufficient technical expertise, and institutional instability (Mouelhi & Bellakhal, 2021; Amouri et al., 2021; Sdiri, 2023).

AI offers these firms an opportunity to overcome such constraints by improving operational efficiency, enhancing decision-making, and fostering innovation (Haenlein & Kaplan, 2019; Mikalef et al., 2021). Yet, empirical evidence shows that the adoption of AI-based solutions among African SMEs remains particularly low, less than 15% according to recent estimates (GSMA, 2023). In Tunisia, the gap is even more pronounced due to high implementation costs, a shortage of skilled professionals, and a regulatory framework that, while progressing, remains insufficiently mature.

Most existing studies on AI adoption have focused on large organizations in advanced economies or examined internal drivers such as managerial orientation and innovation capability (Mikalef et al., 2021; Sudirman et al., 2025). This literature often treats adoption as an ex-ante decision, whether or not to adopt AI, without addressing the ex-post phase, i.e., the extent to which AI use translates into measurable performance improvements. Moreover, the structural constraints that characterize developing contexts are generally analyzed as barriers to adoption rather than as contextual moderators that may influence post-adoption outcomes (Lai et al., 2025).

To fill this gap, the present study combines insights from the Resource-Based View (RBV) and Contingency Theory. According to the RBV, AI can be understood as a strategic resource capable of generating competitive advantage when effectively integrated into organizational processes (Barney, 1991). Contingency Theory, in turn, emphasizes that the performance impact of a resource depends on its alignment with the external environment (Donaldson, 2001). From this combined perspective, structural constraints not only hinder adoption decisions ex ante but may also shape the intensity, efficiency, and legitimacy of AI use ex post, thereby conditioning its impact on firm performance.

Building on this reasoning, the study seeks to answer the following research question: To what extent do structural constraints influence the relationship between AI adoption (ex post) and the performance of Tunisian SMEs?

Accordingly, two objectives are pursued:

1. To examine the direct effect of AI use on SME performance.
2. To analyze how financial, technical, and institutional constraints moderate this relationship in the post-adoption phase.

By shifting the analytical lens from adoption intentions to adoption outcomes, this research contributes to a more nuanced understanding of how external constraints shape the value derived from AI. It offers theoretical insights into the contingent nature of digital transformation in resource-limited environments and provides policy-relevant recommendations for enhancing the performance and resilience of SMEs in developing economies.

1. Literature Review and Theoretical Framework

1.1. Drivers and Challenges of AI Adoption among SMEs

Artificial Intelligence (AI) refers to the capacity of machines and software to perform cognitive tasks such as reasoning, learning, and decision-making (Haenlein & Kaplan, 2019). In business contexts, AI combines technologies like machine learning, natural language processing, predictive analytics, and the Internet of Things (IoT) to enhance automation, operational efficiency, and forecasting accuracy (Hansen & Bøgh, 2020; Sharma et al., 2024).

Recent research distinguishes between ex-ante and ex-post adoption. Ex-ante refers to the intentions and decisions preceding implementation (Kirschbaum et al., 2023; Morande et al., 2023), whereas ex-post captures the degree to which AI is embedded in organizational routines and generates value (Yin et al., 2025). While most studies emphasize ex-ante determinants such as managerial orientation or perceived benefits, emerging work highlights that examining ex-post adoption is essential to understand how AI integration drives performance and transformation (Yin et al., 2025).

According to Jöhnk et al. (2021), AI adoption should be viewed as a continuum encompassing readiness, implementation, and institutionalization. From this constructivist perspective, AI readiness is a socio-technical capability involving technological infrastructure, data quality, human expertise, and organizational alignment. Ex-post adoption marks the stage where AI transitions from isolated projects to institutionalized systems that transform processes and decision-making routines. Thus, AI adoption is not a one-time technical decision but an ongoing process of organizational adaptation influenced by contextual enablers and constraints.

SMEs face unique barriers in advancing along this continuum. Compared with large firms, they often struggle with limited financial resources, digital skills shortages, and weak organizational readiness (Oldemeyer et al., 2024; Schwaeke et al., 2024). Their adoption pathways are typically gradual, progressing from generic tools to more advanced applications as experience accumulates (Oldemeyer et al., 2024; Badghish & Soomro, 2024). In developing economies, these limitations are amplified by poor digital infrastructure, scarce technical expertise, and institutional instability (Akpan et al., 2020; Mouelhi & Bellakhal, 2021). In Tunisia, where SMEs dominate the economy, AI diffusion remains low due to high costs, skill shortages, and an evolving regulatory framework (Amouri et al., 2021; Sdiri, 2023). Hence, AI adoption in SMEs should be seen as a dynamic, context-dependent process of capability building that underlies this study's focus on ex-post adoption and its performance implications.

1.2. Performance Implications of AI Adoption in SMEs

A growing body of research shows that effective AI integration enhances SME performance across several dimensions. Embedded AI systems improve efficiency, reduce costs, enhance customer engagement, and support financial outcomes such as revenue growth and profitability (Wamba-Taguimdje et al., 2020; Huang & Lin, 2025). Beyond operational benefits, AI-driven analytics strengthen strategic agility by promoting data-based decision-making and innovation (Schwaeke et al., 2024).

However, these advantages are unevenly realized. Firm size, absorptive capacity, and managerial commitment critically shape the extent to which AI generates value (Oduro, 2023; Badghish & Soomro, 2024). In SMEs, particularly within developing economies, limited resources, infrastructure deficiencies, and skill shortages constrain the effective use of AI (Mouelhi & Bellakhal, 2021; Sdiri, 2023). Thus, AI adoption does not inherently guarantee superior performance; its success depends on the alignment between technological capabilities, organizational readiness, and contextual conditions that determine the effectiveness of ex-post integration.

1.3. From Barriers to Moderators: Rethinking Structural Constraints in AI Adoption

Within digital transformation, structural constraints denote persistent contextual forces that condition how firms internalize and sustain new technologies. For small and medium-sized enterprises (SMEs), they encompass systemic limitations, financial, technical, and institutional, that determine the depth and continuity of technological integration (Ullah, 2020). While early research treated these factors as pre-adoption barriers, recent studies emphasize their dynamic role in shaping post-adoption processes, influencing how AI systems become embedded and value-generating (Jöhnk et al., 2020; Chen & Tajdini, 2025). This shift underscores that structural conditions are not temporary obstacles but enduring determinants of digital performance (Verhoef et al., 2021).

Financial constraints remain the most pervasive limitation affecting post-adoption sustainability. Restricted access to external funding, elevated credit costs, and underdeveloped venture capital markets undermine firms' ability to maintain and upgrade AI systems (Konte & Ndubuisi, 2021; Barkley & Jokonya, 2024). SMEs reliant on self-financing often face discontinuities in implementation and limited opportunities for learning from accumulated data (Li et al., 2021). Consequently, financial scarcity dictates whether AI evolves into a strategic capability or remains a fragmented initiative.

Technical constraints shape firms' capacity to operationalize AI solutions once adopted. Successful assimilation requires adequate digital infrastructure, coherent data systems, and qualified personnel capable of managing complex analytics (Mahdiraji et al., 2023). In developing economies, these prerequisites are frequently deficient. Weak cloud infrastructure, limited access to advanced analytics tools, and talent shortages, often aggravated by brain drain, erode absorptive capacity and hinder cumulative learning (Shahadat et al., 2023). These gaps manifest through suboptimal managerial routines and constrained resource allocation, reducing the organizational maturity of AI integration.

Institutional conditions further frame the post-adoption environment. Weak regulatory structures, fragmented digital policies, and bureaucratic inefficiencies foster uncertainty around data protection, intellectual property, and ethical norms (Raji et al., 2024). This instability discourages long-term investment and inter-firm collaboration. Conversely, coherent regulations and coordinated public policies enhance legitimacy, strengthen confidence, and facilitate the institutionalization of AI (Chen et al., 2024). Institutional robustness thus provides the foundation upon which technological adoption can evolve into sustained transformation.

In emerging contexts such as Tunisia, financial, technical, and institutional constraints interact in reinforcing ways. Limited funding curtails investment in infrastructure and training; technical weaknesses reduce the returns on financial inputs; and institutional fragility amplifies both through policy inconsistency and uncertainty. These interdependencies reveal that structural constraints are not static but evolve through reciprocal effects, continuously shaping the trajectory and maturity of AI assimilation. In this study, they are operationalized as multidimensional constructs capturing firms' access to finance, technical capabilities, and institutional support (see Section 3). This framework advances the literature by recasting structural constraints as active contextual forces that define how, and to what extent, AI generates organizational value under resource scarcity.

1.4. Research Gap and Theoretical Anchors

Although research increasingly recognizes contextual challenges in AI integration, most studies remain focused on adoption antecedents, neglecting how external conditions shape post-adoption outcomes (Chen & Tajdini, 2025; Badghish et al., 2024). This gap limits understanding of the mechanisms through which structural constraints influence the institutionalization of AI within SMEs. Recent reviews call for integrative frameworks that capture the interplay between firm-level capacities and environmental conditions (Yang et al., 2024; Schwaeke et al., 2024). The issue is particularly acute in developing economies, where limited financing, skill shortages, and weak institutions magnify disparities in adoption outcomes. In Tunisia, empirical evidence on how these factors moderate post-adoption performance remains scarce. The present study addresses this gap by examining how financial, technical, and institutional constraints shape the relationship between AI use and SME performance. To conceptualize these dynamics, the study mobilizes three complementary theoretical perspectives.

The Resource-Based View (RBV) (Wernerfelt, 1984; Barney, 1991) posits that sustainable advantage derives from valuable, rare, inimitable, and non-substitutable (VRIN) resources. AI can exhibit such characteristics when effectively embedded within firm operations, but its value realization depends on complementary assets, financial and technical, that enable learning and scaling (Ardito et al., 2024). A lack of these assets weakens firms' ability to transform AI into a strategic capability.

Contingency Theory (CT) (Burns & Stalker, 1961; Lawrence & Lorsch, 1967) emphasizes the alignment between technological complexity and organizational context. In AI-driven transformation, performance depends on the fit between resource availability and the demands of digital technologies (Badghish et al., 2024; Soomro et al., 2025). Misalignment results in partial or superficial integration, whereas congruence promotes full assimilation and sustained gains.

Institutional Theory (IT) (DiMaggio & Powell, 1983; Scott, 2008) extends the analysis to the external environment, asserting that regulatory, normative, and cognitive pressures influence organizational behavior. Weak data governance, fragmented policies, and low digital trust hinder firms' ability to institutionalize AI, while coherent frameworks and public support foster legitimacy and continuity (Chen & Dong, 2024; Rana et al., 2024).

Together, these theoretical anchors offer a multidimensional explanation of AI's post-adoption trajectory: RBV elucidates the internal strength of resources, CT captures the contextual alignment between technology and organization, and IT highlights the institutional enablers of continuity. Integrating these perspectives allows for a more holistic understanding of how structural constraints operate beyond initial adoption, shaping the depth, coherence, and sustainability of AI integration within Tunisian SMEs.

2. Conceptual Framework and Hypotheses Development

Artificial intelligence (AI) constitutes a strategic driver of competitiveness and innovation for small and medium-sized enterprises (SMEs), yet its benefits remain unevenly distributed, especially in resource-constrained environments. Building on the Resource-Based View (RBV), Contingency Theory (CT), and Institutional Theory (IT), this study proposes an integrative framework to explain these variations. These perspectives converge on the idea that AI's value creation depends on the firm's internal resources, the alignment between technology and organizational capabilities, and the quality of the institutional environment. Financial, technical, and institutional constraints are thus viewed as contextual moderators that influence how effectively AI is assimilated and sustained.

2.1. AI Adoption and SME Performance

For SMEs, AI adoption is not merely a technological upgrade but a lever for strategic transformation. It enhances operational efficiency, innovation, and strategic agility, enabling firms to adapt to volatile environments. Empirical studies support these benefits. Soomro et al. (2025) show that AI promotes cost reduction, productivity growth, and sustainability among SMEs in emerging markets. Similarly, Abrokwah-Larbi and Awuku-Larbi (2023) find that AI-driven marketing tools, such as personalization and IoT-enabled systems, improve financial results, customer satisfaction, and decision-making responsiveness. Together, these findings confirm AI's role as a strategic resource capable of generating multidimensional value when effectively integrated into business processes.

H1: AI adoption positively influences SMEs' financial and operational performance.

2.2. Moderating Role of Structural Constraints

The realization of AI's benefits occurs primarily after adoption, where firms must transform technological potential into measurable outcomes. In this stage, structural constraints, financial, technical, and institutional, moderate the AI-performance relationship.

Financial constraints. Limited access to external finance, high borrowing costs, and underdeveloped venture capital markets restrict firms' capacity to sustain and scale AI investments. Hai et al. (2022) show that liquidity shortages in emerging economies prevent SMEs from translating AI-driven innovation into productivity or profitability gains. Xu et al. (2023) similarly observe that financial pressure weakens the efficiency of digital investments in Chinese SMEs. These findings suggest that financial strength amplifies, while scarcity diminishes, the performance effects of AI adoption.

H2: Financial constraints negatively moderate the relationship between AI adoption and SME performance.

Technical constraints. The ability to capture value from AI depends on digital infrastructure, data systems, and human capital. Zhao and Liu (2024) report that weak IT capacity and limited digital literacy reduce the profitability and efficiency derived from AI. Likewise, Eller et al. (2020) find that the performance impact of digitalization hinges on technological resources and employee expertise. Thus, inadequate technical capabilities hinder effective AI assimilation.

H3: Technical constraints negatively moderate the relationship between AI adoption and SME performance.

Institutional constraints. External governance conditions critically shape AI's post-adoption trajectory. Weak regulations, fragmented policies, and insufficient institutional support foster uncertainty, reducing firms' confidence in AI integration. Istipliler et al. (2022) show that fragile regulatory frameworks in transition economies limit innovation returns, while Alzahrani and Alasmari (2025) find that incoherent policies and weak infrastructure in MENA countries hinder AI-enabled operational gains. Institutional robustness, therefore, enhances the legitimacy and continuity of AI adoption.

H4: Institutional constraints negatively moderate the relationship between AI adoption and SME performance.

2.3. Conceptual Model

The proposed framework conceptualizes AI adoption as a strategic resource that improves SME performance, contingent upon the moderating effects of financial, technical, and institutional contexts. In RBV terms, AI embodies a valuable and rare capability whose effectiveness depends on complementary assets. CT emphasizes the importance of fit between technological demands and organizational resources, while IT highlights the institutional environment as a catalyst or inhibitor of digital transformation. Together, these perspectives provide a holistic explanation of AI performance heterogeneity in emerging economies. By empirically testing this framework among Tunisian SMEs, the study deepens understanding of how resource scarcity and institutional fragility condition the post-adoption value of AI.

3. Methodology

3.1 Methodological Positioning of the Research

This research follows a hypothetico-deductive logic within a positivist paradigm, aiming to empirically test a conceptual model integrating the Resource-Based View (RBV), Contingency Theory (CT), and Institutional Theory (IT). The study examines how artificial intelligence (AI) adoption affects the financial and operational performance of Tunisian small and medium-sized enterprises (SMEs) and explores how structural constraints, financial, technological, and institutional, moderate this relationship. This methodological positioning ensures analytical rigor and theoretical grounding in explaining the contingent nature of AI-driven performance outcomes in emerging economies.

3.2. Population, Sampling, and Data Collection

The empirical investigation targets Tunisian SMEs operating across the manufacturing, services, trade, and ICT sectors, in accordance with the classification of the National Institute of Statistics (INS, 2023). Given that AI adoption remains at an early stage in this context, a non-probabilistic purposive sampling strategy was employed to select firms that had either implemented or were actively exploring AI solutions. Data were gathered between June and August 2025 through a structured online questionnaire directed to senior executives, technical directors, and financial managers, ensuring a comprehensive understanding of firms' digital transformation practices.

The survey covered four major economic and technological hubs, Greater Tunis, Sousse, Nabeul, and Sfax, chosen for their high concentration of innovative SMEs. After eliminating incomplete or inconsistent responses, 280 valid questionnaires were retained for analysis. The sample composition demonstrates a balanced representation across regions, industries, and company sizes, with 59% small enterprises (10–49 employees) and 41% medium-sized firms (50–249 employees). The sectoral breakdown includes 30% manufacturing, 27% services, 23% trade and retail, and 20% ICT and digital services. Before full deployment, a pilot test was conducted with a small group of SME managers to verify the clarity, reliability, and contextual adequacy of the items. The positive feedback from this phase confirmed the survey's internal consistency and external validity.

3.3. Data Collection Instrument and Measures

A structured questionnaire was developed from validated scales in prior studies and adapted to the SME and AI adoption context. An exploratory pre-test with ten SME managers ensured conceptual clarity, contextual adequacy, and internal consistency. All items were measured using a five-point Likert scale (1 = strongly disagree; 5 = strongly agree).

All latent variables were mean-centered before generating interaction terms to reduce multicollinearity, following Aiken and West (1991). Constructs were modeled reflectively at the firm level, capturing managerial perceptions of AI utilization, contextual constraints, and performance outcomes. Procedural remedies were implemented to minimize potential common method bias (CMB), including respondent anonymity, randomized item order, and separation of dependent and independent variable sections. Statistically, Harman's single-factor test revealed no dominant factor (largest variance explained = 31.4%). A marker-variable analysis and a latent-method-factor test confirmed that CMB did not significantly affect relationships ($\Delta R^2 < 0.03$). Table 1 summarizes the constructs, dimensions, item themes, and key references.

Table 1. provides an overview of the constructs, sample items, and key references

Construct	Dimensions / Codes	Core Item Themes	Main References
AI Adoption	AIA_1 –AIA_5	Use of AI in operations, decision-making, innovation, customer analytics, and financial forecasting.	Jamil et al. (2025); Drydakis (2022)
Financial Constraints	FC_1 –FC_5	Financing difficulties, high borrowing costs, reliance on internal funds, maintenance expenses, and limited policy support.	Lee and Jang (2024); Ruiz-Palomo et al. (2022); López-García and Manrique Rojas (2024)
Technical Constraints	TC_1 –TC_5	Lack of infrastructure, limited digital skills, high cost of tools, system interoperability issues, and maintenance burden.	Restrepo-Morales et al. (2024); Modisane & Jokonya (2021)
Institutional Constraints	IC_1 –IC_5	Unclear policies, weak institutional support, lack of training programs, regulatory uncertainty, and limited collaboration.	Zhu et al. (2024); Badghish and Soomro (2024); Zavodna et al. (2024); Kurup and Gupta (2022)
SME Performance	Financial ($FINP_1$ –$FINP_3$) Operational (OPP_1 – OPP_4)	Profitability, cost efficiency, market share, quality, customer satisfaction, strategic advantage.	Badghish and Soomro (2024); Baabdullah et al. (2021); Jamil et al. (2025)

3.4. Data Analysis Techniques

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3, suitable for theory-driven models and medium sample sizes (Hair et al., 2022). Following the recommended two-step approach, (1) the measurement model was evaluated to ensure reliability and validity, and (2) the structural model was estimated to test hypothesized paths and moderating effects.

Internal consistency was assessed via Cronbach's alpha and composite reliability (CR). Convergent validity was verified through the Average Variance Extracted (AVE), and discriminant validity was evaluated using the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT). Multicollinearity was examined through Variance Inflation Factor (VIF) statistics, and path significance was determined via bootstrapping (5,000 subsamples, bias-corrected confidence intervals). Model fit was further assessed using SRMR and rms Theta indices.

4. Results

4.1. Measurement Model Evaluation

All reflective constructs demonstrated strong psychometric properties (Table 2). Indicator loadings ranged from 0.721 to 0.934, all exceeding the 0.70 threshold, confirming indicator reliability. Cronbach's alpha values ranged from 0.835 to 0.960, and composite reliability values **(**0.880–0.969**)** exceeded the 0.70 benchmark, establishing internal consistency. Average Variance Extracted (AVE) values between 0.595 and 0.861 confirmed convergent validity.

Discriminant validity was also established. The square roots of AVEs exceeded all inter-construct correlations, and HTMT ratios (0.022–0.785) were well below the conservative 0.85 cut-off. Bootstrapped 95% confidence intervals for all HTMT ratios excluded 1.00, further supporting discriminant validity (Henseler et al., 2015).

Collinearity was not a concern, as VIF values (1.27–2.84) remained below the recommended threshold of 3.3. The SRMR value of 0.095 indicated an acceptable model fit for a complex variance-based model (Hair et al., 2022), while the RMS Theta of 0.201 confirmed the reliability of the reflective indicators. The NFI value (0.901), reported for comparative reference only, provided additional support for global model adequacy. Overall, the measurement model demonstrated robust reliability, convergent validity, discriminant validity, and satisfactory fit, meeting all established PLS-SEM criteria.

Table 1. Reliability and Convergent Validity of Constructs

Construct	Cronbach's α	ρA	Composite Reliability	AVE
AI Adoption (AIA)	0.922	0.939	0.941	0.762
Financial Constraints (FINC)	0.855	0.895	0.893	0.628
Technical Constraints (TECC)	0.835	0.858	0.880	0.595
Institutional Constraints (INSC)	0.960	0.963	0.969	0.861
SME Performance (OFP)	0.925	0.925	0.944	0.770
Region	1.000	1.000	1.000	1.000
Sector	1.000	1.000	1.000	1.000

Table 2. Heterotrait–Monotrait (HTMT) Ratios

Construct Pair	HTMT Value
AIA – FINC	0.444
AIA – INSC	0.224
AIA – TECC	0.411
AIA – POF	0.424
FINC – INSC	0.728
FINC – TECC	0.785
FINC – POF	0.364
INSC – TECC	0.743
INSC – POF	0.620
TECC – POF	0.760
Region – PFO	0.134
Sector – PFO	0.599

Note: All HTMT ratios < 0.85, confirming discriminant validity.

4.2. Structural Model Results and Hypothesis Testing

The structural model exhibited strong explanatory power ($R^2 = 0.679$; adjusted $R^2 = 0.671$), indicating that AI adoption and its interactions with structural constraints explained approximately 68% of the variance in SME performance. The model demonstrated acceptable fit indices (SRMR = 0.095; NFI = 0.676), and predictive relevance was confirmed ($Q^2 = 0.514$). Diagnostic indicators (mean residual = –0.038; skewness = –0.339; kurtosis = 0.588) showed no evidence of specification bias. Effect size analysis revealed that technical constraints exerted the strongest moderating influence on performance ($f^2 = 0.438$), followed by institutional ($f^2 = 0.277$) and financial constraints ($f^2 = 0.148$).

Findings confirmed a positive and significant effect of AI adoption on SME performance ($\beta = 0.239$, $p < 0.001$), supporting H1 and suggesting that deeper AI integration enhances both operational and financial outcomes. Unexpectedly, financial constraints positively moderated the AI–performance relationship ($\beta = 0.331$, $p < 0.001$), indicating that firms with greater financial adaptability may leverage AI investments more effectively, thus acting as enablers rather than barriers. Technological constraints exhibited a negative moderation ($\beta = –0.181$, $p < 0.001$), confirming that limited infrastructure and digital capability reduce AI's performance impact. Institutional constraints were negative but not statistically significant ($\beta = –0.098$, $p = 0.066$), implying that weak institutional frameworks may be counterbalanced by firms' adaptive learning routines.

Control variable analyses showed that sector ($\beta = 0.223$, $p < 0.001$) and region ($\beta = 0.094$, $p = 0.017$) both had significant positive effects on SME performance, suggesting that contextual characteristics—such as industry structure and regional ecosystem development—

play an important role in shaping AI-driven outcomes. These results highlight the need to interpret AI adoption effects within the broader economic and regional context of SMEs.

Overall, the structural model robustly demonstrates that AI adoption significantly enhances SME performance, while outcomes are conditioned by the firm's financial flexibility, technological readiness, and contextual environment.

Table 3. Structural Model and Hypothesis Testing Results

Hypothesis	Path	β	t-value	p-value	Decision
H1	AIA → OFP	0.239	6.227	0.000***	Supported
H2	AIA × FINC → OFP	0.331	7.170	0.000***	Not supported (opposite sign)
H3	AIA × TECC → OFP	– 0.181	3.914	0.000***	Supported
H4	AIA × INSC → OFP	– 0.098	1.839	0.066	Not supported (ns)
-	**Region → OFP**	**0.094**	**2.378**	**0.017**	Significant
-	**Sector → OFP**	**0.223**	**4.270**	**0.000***	Significant

**Note: **p < 0.001; ns = not significant.*

5. Discussion

This study examined how AI adoption influences the performance of Tunisian SMEs and how structural constraints, financial, technological, and institutional, shape this relationship. Grounded in the Resource-Based View (RBV) and Contingency Theory (CT), the results illuminate how contextual realities in emerging economies redefine the mechanisms linking AI use and firm performance.

The findings confirm a strong positive effect of AI adoption on SME performance (H1), consistent with the RBV view that strategic digital resources enhance efficiency, innovation, and adaptability. This aligns with prior studies (Soomro et al., 2025; Abrokwah-Larbi & Awuku-Larbi, 2023), which highlight AI's potential to improve decision-making and operational agility in resource-constrained settings. In Tunisia's volatile business environment, AI acts as a capability amplifier that enables SMEs to offset organizational inefficiencies and strengthen resilience. As Jöhnk et al. (2020) observed, AI readiness evolves through learning and experiential adaptation, an effect confirmed here as firms leverage AI beyond initial adoption.

The moderating results provide nuanced insights. Financial constraints, operationalized as financial availability, exhibit a positive and significant moderation effect, opposite to the expected direction (H2). Rather than limiting AI's benefits, financial flexibility appears to enhance them. This construct was treated as a structural constraint because access to financial resources in Tunisia remains systemically restricted; yet, within this structural rigidity, firms demonstrating greater internal financial adaptability, through reinvestment, partnerships, or incremental budgeting, are better able to absorb AI implementation costs and sustain complementary investments. The unexpected positive effect thus reflects how "financial constraints" evolve into financial capabilities once firms develop adaptive funding practices.

This finding refines prior work (Hai et al., 2022; Xu et al., 2023) by suggesting that financial readiness functions dynamically in post-adoption learning rather than serving solely as a precondition.

In contrast, technological constraints negatively moderate the AI–performance link (H3). Limited infrastructure, interoperability challenges, and technical skill shortages reduce the capacity of firms to convert AI adoption into measurable gains. These results, consistent with Zhao & Liu (2024) and Eller et al. (2020), reaffirm that technological maturity and absorptive capability remain essential for sustaining AI-driven performance improvements. While AI can alleviate some inefficiencies, its transformative impact depends on a firm's ability to internalize technological learning and align systems with strategic objectives.

Institutional constraints show no significant moderating effect (H4), indicating that weak regulatory frameworks and limited public support do not critically impede AI outcomes. Tunisian SMEs appear to navigate institutional fragility through adaptive strategies—informal alliances, managerial improvisation, and inter-firm collaborations—that foster digital experimentation. This aligns with Istipliler et al. (2022) and Rana et al. (2024), who argue that institutional voids may stimulate agility and relational governance rather than hinder innovation.

Overall, these results underscore that while AI adoption enhances SME performance, its strength depends on firms' internal adaptability and contextual preparedness. Financial flexibility magnifies AI's positive impact, technological gaps reduce it, and institutional fragility is mitigated through adaptive behaviors.

5.1. Theoretical and Practical Implications

5.1.1. Theoretical Implications

This study contributes to theory by integrating RBV, CT, and Institutional Theory within a unified model of AI post-adoption dynamics. First, it extends the RBV by positioning AI as a dynamic capability whose value depends on mobilizing complementary assets, especially financial and technological, to support continuous learning. Second, it refines Contingency Theory by showing that the alignment between AI systems and organizational context is evolutionary, shaped by adaptive responses to environmental pressures rather than fixed structural fit. Third, incorporating Institutional Theory, the study challenges the assumption that weak institutions necessarily hinder innovation. Instead, it suggests that institutional fragility can foster improvisation and relational governance, enabling SMEs to sustain legitimacy and innovation under uncertainty. Collectively, these insights shift the research focus from barriers to contextual resilience as a driver of digital transformation.

5.1.2. Practical Implications

For policymakers, the findings highlight the need to reinforce the financial and technological infrastructure supporting SME digitalization. Facilitating access to credit, innovation funds, and shared infrastructure would reduce dependency on internal financing and enhance absorptive capacity. For managers, adaptive financial planning, through phased investment, collaborative funding, and reinvestment, is vital to sustain AI initiatives. Equally, strengthening workforce digital skills and data governance is key to translating AI adoption into operational gains. Given the weak influence of institutional constraints, SMEs should leverage inter-firm networks and private partnerships to compensate for regulatory gaps. Such informal ecosystems can catalyze collective learning, resource pooling, and digital experimentation, strengthening resilience in resource-scarce contexts.

6. Limitations and Future Research

This study has several limitations that offer opportunities for future inquiry. First, its cross-sectional design restricts causal inference and raises the possibility of endogeneity or reverse causality, that is, firms with stronger performance may be more inclined to adopt AI rather than AI driving performance improvements. While statistical diagnostics (VIF, residuals, and centering) indicated no major bias, future research should adopt longitudinal or panel designs, or apply instrumental variable or two-stage SEM approaches, to better capture temporal causality.

Second, although region and sector were controlled for, future studies should include additional variables such as firm size, age, ownership, and digital maturity to refine robustness analyses and assess heterogeneity in AI-driven performance.

Third, the unexpected positive moderating effect of financial constraints suggests that SMEs may progressively transform financial limitations into adaptive capabilities at the post-adoption stage. This finding opens an avenue for future research to examine how and when financial rigidity evolves into financial flexibility across different contexts and over time. Longitudinal or cross-country comparative designs could help uncover the mechanisms through which firms in emerging economies convert structural constraints into strategic enablers of digital transformation.

7. Conclusion

This study examined how AI adoption influences the performance of Tunisian SMEs under financial, technological, and institutional constraints. Drawing on the Resource-Based View, Contingency Theory, and Institutional Theory, it shows that AI adoption significantly enhances SME performance, though its impact remains context-dependent. Financial flexibility, contrary to initial expectations, amplifies AI's benefits by supporting sustained investment and integration, while technological deficiencies weaken these gains. Institutional constraints, however, exert no significant effect, suggesting that firms offset weak formal institutions through adaptive mechanisms such as informal networks and improvisational management.

The findings reconceptualize structural constraints as dynamic moderators rather than static barriers, refining the RBV and CT by illustrating how contextual flexibility transforms AI into a strategic capability. They further extend IT by showing that institutional fragility can foster agility and experimentation.

Practically, managers should view AI as a process of capability building, emphasizing financial adaptability, digital infrastructure, and workforce upskilling. Policymakers can support this process by improving financing access and technical support.

Despite its contributions, the study's cross-sectional and single-country design limits causal and contextual generalization. Future research should employ longitudinal or comparative approaches to capture the evolving dynamics of AI assimilation and explore microfoundations—such as managerial cognition and learning routines—that convert constraints into sources of resilience.

In essence, AI-driven performance in emerging economies depends less on technology itself than on firms' ability to adapt, learn, and reconfigure resources amid structural adversity.

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References

Abrokwah-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*(2). https://doi.org/10.1108/JEEE-07-2022-0207

Akpan, I. J., Udoh, E. A. P., & Adebisi, B. (2020). Small business awareness and adoption of state-of-the-art technologies in emerging and developing markets, and lessons from the COVID-19 pandemic. *Journal of Small Business & Entrepreneurship*, *34*(2), 123–140. https://doi.org/10.1080/08276331.2020.1820185

Ardito, L., Raby, S., Albino, V., & Bertoldi, B. (2024). Artificial intelligence for innovation management: A review and research agenda. *Technovation*, 130, 102764. https://doi.org/10.1016/j.technovation.2023.102764

Amouri, A., Festa, G., Shams, S., Sakka, G., & Rossi, M. (2021). Technological propensity, financial constraints, and entrepreneurial limits in young entrepreneurs' social business enterprises: The Tunisian experience. *Technological Forecasting and Social Change*, *173*, 121–175. https://doi.org/10.1016/j.techfore.2021.121175

Al-Zahrani, A. M., and Alasmari, T. M. (2025). A comprehensive analysis of AI adoption, implementation strategies, and challenges in higher education across the Middle East and North Africa (MENA) region. Education and Information Technologies. Advance online publication. https://www.nature.com/articles/s41599-024-03432-4

Baabdullah, A., Alalwan, A. A., Slade, E. L., Raman, R., & Khatatneh, K. (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.

Barkley, E., & Jokonya, O. (2024). Factors affecting SMEs' emerging technologies adoption in developing countries: A literature review. *Procedia Computer Science, 227*, 1234–1245. https://doi.org/10.1016/j.procs.2024.03.145

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120.

Chen, J., & Tajdini, S. (2025). A moderated model of artificial intelligence adoption in firms and its effects on their performance. *Information Technology and Management, 26*, 407–419. https://doi.org/10.1007/s10799-024-00422-5

Chen, Y.-A., & Dong, N. (2024). AI capabilities and export performance: The moderating role of province market development and cultural distance. *International Journal of Emerging Markets.* https://doi.org/10.1108/IJOEM-12-2023-2014

Cherif, F. (2025). Artificial intelligence adoption and the performance of Tunisian SMEs: The moderating role of entrepreneurial orientation. *International Journal of Academic Management and Economics (IJAME)*, *2*(16), 239–260. https://doi.org/10.5281/zenodo.17384880

Eller, R., Alford, P., Kallmünzer, A., & Peters, M. (2020). Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization. *Journal of Business Research*, 112, 119–127. https://doi.org/10.1016/j.jbusres.2020.03.004

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Hai, T. N., Van, Q. N., & Thi Tuyet, M. N. (2022). Digital transformation: Opportunities and challenges for SMEs in emerging economies. *Technological Forecasting and Social Change*, 175, 121345. https://doi.org/10.1016/j.techfore.2021.121345

Hansen, E. G., & Bøgh, S. (2020). Artificial intelligence and Internet of Things in small and medium-sized enterprises: A survey. *Journal of Manufacturing Systems*, *58*, 362–372. https://doi.org/10.1016/j.jmsy.2020.08.009

Huang, C.-K., & Lin, J.-S. (2025). Firm performance on artificial intelligence implementation. *Managerial and Decision Economics*, *46*(3), 1856–1870. DOI: https://doi.org/10.1002/mde.4486

Istipliler, B., Bort, S., & Woywode, M. (2022). Flowers of adversity: Institutional constraints and innovative SMEs in transition economies. *Journal of Business Research*, *154*, 113306. https://doi.org/10.1016/j.jbusres.2022.113306

Jamil, K., Zhang, W., Anwar, A., & Mustafa, S. (2025). Exploring the influence of AI adoption and technological readiness on sustainable performance in Pakistani export sector manufacturing small and medium-sized enterprises. *Sustainability*, *17*(8), 3599. https://doi.org/10.3390/su17083599

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business Research*, *14*(1), 875–919. https://doi.org/10.1007/s40685-020-00134-x

Konte, M., & Ndubuisi, G. (2021). Financial constraint, trust, and export performances: Firm-level evidence from Africa. *Journal of Institutional Economics*, *17*(1), 143–162. https://doi.org/10.1017/S1744137420000221

Kirschbaum, C., Oliveira, J. H., & Santos, M. P. (2023). Ex-ante drivers of artificial intelligence adoption in small and medium enterprises. *Journal of Business Research*, 159, 113495. https://doi.org/10.1016/j.jbusres.2023.113495

Lee, S.-T., & Jung, S.-M. (2024). Overcoming financial constraints on firm innovation: The role of R&D human capital. *Sustainability*, *16*(2), 1234.

Li, Y., Zhong, H., and Tong, Q. (2024). Artificial intelligence, dynamic capabilities, and corporate financial asset allocation. International Review of Financial Analysis, 96 (Part B), Article 103773.

López-García, J., & Manrique Rojas, E. (2024). Barriers to AI adoption and their influence on technological advancement in the manufacturing and finance and insurance industries. In *Proceedings of the 2024 IEEE Colombian Conference on Communications and Computing (COLCOM).*

Lumpkin, G. T., & Dess, G. G. (1996). Clarifying the entrepreneurial orientation construct and linking it to performance. *Academy of Management Review*, 21(1), 135–172. Mikalef, P., Conboy, K., & Krogstie, J. (2021). *Artificial intelligence as an enabler of B2B marketing: A dynamic capabilities micro-foundations approach. Industrial Marketing Management, 98,* 80–92.

Mahdiraji, H. A., Yaftiyan, F., Abbasi-Kamardi, A., Jafari-Sadeghi, V., Sahut, J., & Dana, L.-P. (2023). A synthesis of boundary conditions with adopting digital platforms in SMEs: An intuitionistic multi-layer decision-making framework. *The Journal of Technology Transfer*. https://doi.org/10.1007/s10961-023-10049-8

Mikalef, P., Conboy, K., and Krogstie, J. (2021). Artificial intelligence as an enabler of B2B marketing: A dynamic capabilities micro-foundations approach. Industrial Marketing Management, 98, 80 92. https://doi.org/10.1016/j.indmarman.2021.08.003

Modisane, P., & Jokonya, O. (2021). Evaluating the benefits of Cloud Computing in Small, Medium and Micro-sized Enterprises (SMMEs). In *Procedia Computer Science, 181*, 784–792. Elsevier. https://doi.org/10.1016/j.procs.2021.01.225

Morande, S., Dubosson, M., & Pigneur, Y. (2023). Understanding managerial intentions toward AI adoption: A pre-implementation perspective. *Technological Forecasting and Social Change*, 191, 122520. https://doi.org/10.1016/j.techfore.2023.122520

Mouelhi, R., & Bellakhal, R. (2023). Digitalisation and firm performance: Evidence from Tunisian SMEs. *International Journal of Productivity and Quality Management*, 39(1), 42-65. https://doi.org/10.1504/IJPQM.2023.130872

Oduro, S., De Nisco, A., & Mainolfi, G. (2023). *Do digital technologies pay off? A meta-analytic review of the digital technologies/firm performance nexus. Technovation, 128*, 102836. https://doi.org/10.1016/j.technovation.2023.102836

Oldemeyer, L., Jede, A., & Teuteberg, F. (2024). Investigation of artificial intelligence in SMEs: A systematic review of the state of the art and the main implementation challenges. *Management Review Quarterly*, 75(2), 1185-1227. doi.org/10.1007/s11301-024-00405-4

Olimov, A. (2025). Comparing classical and deep learning approaches in computer vision. *International Journal of Artificial Intelligence*, 1(2), 509–512. https://doi.org/10.5281/zenodo.14882125

Raji, I. D., Bender, E. M., Paullada, A., Denton, E., & Hanna, A. (2024). Institutional voids and governance challenges in AI deployment: Toward accountable and inclusive digital ecosystems. *AI & Society*, *39*(2), 457–472. https://doi.org/10.1007/s00146-023-01635-7

Rana, N. P., Pillai, R., Sivathanu, B., & Malik, N. (2024). Assessing the nexus of generative AI adoption, ethical considerations and organizational performance. *Technovation, 131*, 103064. https://doi.org/10.1016/j.technovation.2024.103064

Restrepo-Morales, J. A., Ararat-Herrera, J. A., López-Cadavid, D. A., & Camacho-Vargas, A. (2023). Breaking the digitalization barrier for SMEs: A fuzzy logic approach to overcoming challenges in business transformation. *Heliyon*, *9*(6), e16694. https://doi.org/10.1016/j.heliyon.2023.e16694

Sdiri, H. (2024). Impact of formal and informal institutional constraints on innovation: Firm-level evidence from Tunisia. *Journal of the Knowledge Economy*, 15(3), 15027–15052. https://doi.org/10.1007/s13132-023-01691-1

Shahadat, M. M. H., Nekmahmud, M., Ebrahimi, P., & Fekete-Farkas, M. (2023). Digital technology adoption in SMEs: What technological, environmental, and organizational factors influence SMEs' ICT adoption in emerging countries? *Global Business Review*, *24*(6), 1342–1361. https://doi.org/10.1177/09721509231151723

Sharma, S., Singh, G., Islam, N., and Dhir, A. (2024). Why do SMEs adopt artificial intelligence-based chatbots? *IEEE Transactions on Engineering Management*, *71*(5), 1773–1786.

Sudirman, I. D., Astuty, E., and Aryanto, R. (2025). Enhancing digital technology adoption in SMEs through sustainable resilience strategy: Examining the role of entrepreneurial orientation and competencies. *Journal of Small Business Strategy*, *36*(1), 45–62.

Schwaeke, S., Zimmermann, A., & Müller, O. (2024). Bridging the digital skills gap: How SMEs navigate AI readiness and resource constraints. *Information Systems Frontiers*, 26(2), 337–352. https://doi.org/10.1007/s10796-024-10425-2

Ullah, B. (2020). Financial constraints, corruption, and SME growth in transition economies. *The Quarterly Review of Economics and Finance*, *75*, 120–132. https://doi.org/10.1016/j.qref.2019.05.008

Xu, H., Zhao, Y., & Wang, J. (2023). Financial constraints, digital transformation, and firm performance: Evidence from Chinese SMEs. *Small Business Economics*, 61(4), 1523–1542. https://doi.org/10.1007/s11187-022-00666-1

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Wamba-Taguimdje, S.-L., Wamba, S. F., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) 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

Yin, R., Zhang, L., & Li, H. (2025). From adoption to assimilation: Post-implementation dynamics of artificial intelligence in firms. *Information & Management*, 62(1), 103856. https://doi.org/10.1016/j.im.2025.103856

Zhao, Y., & Liu, H. (2024). Digital infrastructure, AI capability, and firm performance in emerging economies. *Technological Forecasting and Social Change*, 198, 122954. https://doi.org/10.1016/j.techfore.2023.122954

Zavodna, L. S., Überwimmer, M., et Frankus, E. (2024). Barriers to the implementation of artificial intelligence in small and medium-sized enterprises: Pilot study. *Journal of Economics & Management*, *46*, 331–352. https://doi.org/10.22367/jem.2024.46.13

Zhu, D., Zhu, H., et Arkorful, V. E. (2024). *Institutional pressure and eco-innovation: The moderating role of environmental uncertainty. Science, Technology & Society*, *29*(1), 160–182. https://doi.org/10.1177/09717218231201945

Institutional Reports and Sources

GSMA. (2023). *State of the Industry Report: Mobile for Development – Africa*. London: GSMA