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Artificial Intelligence Adoption and the Performance of Tunisian SMEs: The Moderating Role of Entrepreneurial Orientation.

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Abstract*:*

This study investigates the impact of artificial intelligence (AI) adoption on the performance of small and medium-sized enterprises (SMEs), with a particular focus on the moderating role of entrepreneurial orientation (EO). The research is motivated by the growing imperative for firms in resource-constrained economies to leverage digital technologies as a means of sustaining competitiveness. Survey data were collected from 250 SMEs across key economic regions and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The empirical findings reveal that AI adoption exerts a significant positive effect on firm performance, particularly by enhancing operational efficiency and improving financial outcomes. Furthermore, EO strengthens this relationship by fostering adaptive learning, resource orchestration, and strategic responsiveness to environmental turbulence. The study contributes to the digital transformation literature by extending theory to an emerging economy context and demonstrating how organizational posture conditions the benefits of AI integration. Beyond theoretical contributions, the results offer concrete guidance for decision-makers: managers are encouraged to complement technological investments with entrepreneurial capabilities, while policymakers are advised to create supportive ecosystems that facilitate AI diffusion. Together, these insights show that AI adoption, when combined with an entrepreneurial mindset, can serve as a pathway toward resilience, growth, and sustainable competitive advantage.

Keywords*:* Artificial intelligence, SME performance, entrepreneurial orientation, dynamic capabilities, Tunisia.

Introduction

In the era of digital transformation, competitive survival increasingly depends on innovation. Small and medium-sized enterprises (SMEs) in emerging economies face the dual challenge of resource scarcity and technological adaptation (Gouveia et al., 2024). In Tunisia, SMEs represent more than 90% of firms and account for about 40% of private sector employment (INS, 2023). Yet they operate under mounting pressures, including high inflation (8.5% in 2023), intensified global competition, and structural barriers such as limited access to finance, shortages of technical expertise, and institutional complexity (Central Bank of Tunisia, 2023; World Bank, 2022; UTICA, 2023). These constraints highlight the strategic importance of digital technologies for sustaining competitiveness.

Among advanced technologies, artificial intelligence (AI) is increasingly recognized as a transformative force. Defined as computational systems that emulate human cognition (Haenlein and Kaplan, 2019), AI can enhance efficiency, automate processes, improve forecasting, and strengthen customer engagement. Empirical evidence demonstrates productivity gains: generative AI tools raise worker output by 14% (Brynjolfsson et al., 2023), while AI-assisted tasks are completed 25% faster with 40% higher quality (Dell'Acqua et al., 2023). Despite such promise, adoption remains limited in Africa, with only about 12% of SMEs effectively using AI, due to high costs, insufficient capabilities, and weak policy support (GSMA, 2023; Ransbotham et al., 2022). To control for these contextual constraints, this study incorporates financial, technical, and regulatory factors into its model.

Most prior research on AI adoption has focused on large corporations, leaving the SME context, especially in emerging economies, relatively underexplored (Sharma et al., 2021; Khan et al., 2024). In volatile and resource-constrained environments, technology availability alone does not guarantee performance gains; value creation depends on firms' ability to mobilize, integrate, and reconfigure resources (Karami et al., 2024). Entrepreneurial orientation (EO), characterized by innovativeness, risk-taking, and proactiveness (Covin & Slevin, 1989), represents a dynamic capability that fosters learning, experimentation, and adaptability, and may thus enable SMEs to unlock the strategic value of AI adoption (Teece, 2014; Sudirman et al., 2025). This research addresses the lack of empirical investigation of how EO moderates the AI-performance relationship in SMEs from emerging economies, positioning Tunisia as a critical case. Evidence from related domains suggests that EO strengthens the performance effects of digital technologies such as e-commerce (Abebe, 2014), social media (Fang et al., 2021), and broader transformation initiatives (Vrontis et al., 2022). Although recent work recognizes EO as a driver of AI adoption

and firm outcomes (Hurby, 2024), its moderating effect on the AI-performance link has not been empirically tested in resource-constrained settings. By addressing this gap, the study contributes to a better understanding of how organizational posture shapes the benefits of digital transformation.

Theoretically, the study builds on the Resource-Based View (RBV), which conceptualizes AI as a strategic resource, and on Dynamic Capabilities Theory (DCT), which emphasizes how EO enables firms to reconfigure assets under uncertainty. Accordingly, the research pursues two objectives: (1) to examine the effect of AI adoption on SME performance, and (2) to investigate the moderating role of EO in this relationship, while incorporating structural constraints as control variables. Methodologically, the study draws on survey data from 250 SMEs across Tunisia's main economic regions and applies Partial Least Squares Structural Equation Modeling (PLS-SEM), a method suited for small samples and non-normal data common in SME research. Practically, it offers insights for managers and policymakers seeking to foster resilience, growth, and sustainable competitiveness through AI-enabled strategies.

The remainder of this article is organized as follows: Section 2 reviews the literature on AI, performance, and EO; Section 3 develops the conceptual framework and hypotheses; Section 4 presents the methodology; Section 5 reports the findings; Section 6 discusses theoretical and managerial implications; and Section 7 concludes with directions for future research.

1. Literature Review and Theoretical Framework

1.1.Operationalizing Artificial Intelligence in SMEs: A Multidimensional Perspective

Artificial intelligence (AI) encompasses technologies that emulate human cognition, such as learning, perception, and decision-making, enabling organizations to enhance efficiency, accuracy, and automation through predictive analytics, intelligent agents, and optimization tools (Russell and Norvig, 2020). In Tunisian SMEs, a vital component of national production and employment, the benefits of AI remain constrained by infrastructural weaknesses, talent shortages, and limited strategic maturity. These contextual constraints, while peripheral to the theoretical model, are included as control variables to isolate the specific effects of AI adoption and firm capabilities on performance (Yusuf et al., 2024; Zebec & Stemberger, 2020).

AI adoption is increasingly viewed as a multidimensional process rather than a binary choice. The technological dimension reflects the extent of AI use in operations and decision-support systems (DeStefano et al., 2022; Yin et al., 2023); the strategic dimension concerns its integration into broader organizational goals (Jankovic & Curović, 2023); and the absorptive capacity dimension

captures firms' ability to acquire, assimilate, and exploit AI-related knowledge through expertise and adaptive routines (Qu & Kim, 2025). This multidimensional view clarifies why firms with comparable digital access achieve divergent outcomes and underscores the central role of internal capabilities in AI-driven transformation.

1.2.Barriers to AI Adoption in Tunisian SMEs

Although artificial intelligence (AI) holds strong potential to enhance SME performance, its adoption in Tunisia remains constrained by interrelated financial, technical, and institutional barriers. Financially, high upfront costs for software, cloud infrastructure, and maintenance, which can absorb up to 30% of annual innovation budgets in emerging markets (Badghish and Soomro, 2024), generate uncertainty about returns, especially for resource-limited firms (Ghobakhloo and Tang, 2019), a concern reinforced by the absence of fiscal incentives and governmental support (Dwivedi et al., 2021). Technically, severe shortages in data science and machine learning expertise undermine absorptive capacity, further aggravated by brain drain and limited talent pipelines (Dey et al., 2023), though some firms mitigate these constraints through outsourcing, collaboration, or informal learning networks (Upadhyay et al., 2022). At the institutional level, weak regulatory and governance frameworks concerning data use, transparency, and liability discourage adoption; in Tunisia, 63% of SME leaders cite regulatory uncertainty as a major impediment (Ransbotham et al., 2022; World Bank, 2023), reflecting a persistent misalignment between policy frameworks and SMEs' operational realities (Segarra-Blasco et al., 2025). While not central to the theoretical model, these structural constraints are incorporated as control variables to account for their potential influence in the empirical analysis.

1.3. Entrepreneurial Orientation as a Strategic Capability in AI Adoption

In structurally constrained environments, the adoption of artificial intelligence (AI) in small and medium-sized enterprises (SMEs) depends not only on external conditions but also on internal strategic factors, particularly entrepreneurial orientation (EO) (Nasution et al., 2021; Upadhyay et al., 2022). EO reflects a firm's posture toward innovation, risk-taking, and proactiveness (Miller, 1983; Covin and Slevin, 1989), and has increasingly been conceptualized as a dynamic capability that supports adaptation and resource reconfiguration under uncertainty (Octasylva et al., 2023).

In the context of AI, entrepreneurial orientation enhances the ability of SMEs to align emerging technologies with strategic objectives. By fostering foresight and learning agility, EO facilitates the reconfiguration of organizational routines and processes required for effective AI deployment (Teece, 2014; Abdul Wahab and Radmehr, 2024). Empirical studies confirm that firms with higher

EO are more inclined to embrace AI tools and achieve superior outcomes, even in resource-constrained settings (Hruby, 2024; Kraus et al., 2018). Hruby's (2024) work in the Czech chemical sector illustrates that EO enables firms to integrate AI despite structural limitations, while Abdul Wahab and Radmehr (2024) show that absorptive capacity and agility, both strongly associated with EO, mediate the performance gains of AI adoption.

Entrepreneurial SMEs frequently pursue frugal strategies such as open-source tools, collaborative networks, and modular platforms to mitigate financial and technical constraints (Wamba-Taguimdje et al., 2021; Ghobakhloo and Tang, 2019). They also invest in hybrid skills and flexible structures, which strengthen their ability to navigate complex institutional and technological landscapes. This agility, often driven by EO, is particularly valuable in emerging economies like Tunisia, where systemic barriers slow digital transformation (Abdul Wahab and Radmehr, 2024; Ransbotham et al., 2022). Building on this evidence, the present study positions EO as a dynamic capability that not only fosters AI adoption but also amplifies the extent to which it translates into measurable performance gains. While EO's facilitating role is well recognized, its moderating effect on the AI-performance link remains underexplored, leaving a conceptual and empirical gap that this research aims to address.

1.4.SME Performance Through Artificial Intelligence Adoption

SME performance refers to the ability to sustain productivity, profitability, and innovation (Fernández-Mesa et al., 2014). In resource-constrained contexts, artificial intelligence (AI) acts as a strategic enabler, enhancing efficiency, competitiveness, and innovation (Assidi et al., 2025). By automating tasks, optimizing supply chains, and supporting data-driven decision-making, AI reduces costs and opens new revenue streams through insights into customer behavior (Sharma, 2024; Wamba-Taguimdje, 2020). However, these gains stem not from AI adoption per se but from its strategic integration into organizational processes, aligning with culture, governance, and long-term goals (Teece, 2014; Mikalef et al., 2021). Thus, performance improvements rely on firms' ability to embed AI into routines and decision structures (Dwivedi et al., 2021). For SMEs in emerging economies, institutional and financial constraints make the capacity to absorb, adapt, and leverage AI a key source of competitive advantage. Strategic intent, adaptability, and internal competencies determine whether AI adoption yields tangible outcomes (Yusuf et al., 2021). Moreover, entrepreneurial orientation, through innovation, agility, and proactiveness, amplifies these effects, highlighting the need to theorize how EO conditions the AI-performance relationship, the central focus of this study.

1.5.Research Gap and Theoretical Foundations

Over the past decade, research on digital transformation in SMEs has underscored the pivotal role of artificial intelligence (AI) in enhancing productivity, efficiency, and innovation (Kraus et al., 2018; Mikalef et al., 2021). Within this stream, entrepreneurial orientation (EO) has emerged as a strategic capability that enables firms to effectively adopt and exploit AI, especially under conditions of uncertainty and environmental dynamism (Dubey et al., 2020; Sherla & Sharma, 2024). EO thus operates as a catalyst for leveraging digital technologies to gain a competitive advantage. However, existing studies have primarily conceptualized EO as a direct driver of technology adoption or as a mediator through innovation outcomes (Alhammadi, 2025; Park and Kim, 2025), with limited attention to its potential moderating role in strengthening the link between AI adoption and performance. Recent evidence also highlights contextual contingencies: while dynamic environments may amplify AI's benefits (Dubey et al., 2020; Sherla and Sharma, 2024), certain EO dimensions have exhibited weak or even negative associations with managerial attitudes toward AI (Kukanja, 2024). Furthermore, measurement inconsistencies and the lack of longitudinal evidence continue to limit theoretical refinement and empirical robustness (Hruby, 2024). Taken together, these insights reveal an important and largely unaddressed research deficiency: despite the acknowledged strategic importance of EO, its conditioning effect on the AI-performance relationship remains insufficiently examined. To bridge this shortcoming, the present study draws on the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT) to conceptualize EO as a moderating capability that enhances firms' ability to translate AI adoption into superior performance outcomes.

1.6.Theoretical Foundations: Integrating RBV and DCT

The Resource-Based View (RBV) posits that firms achieve sustained competitive advantage by leveraging resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). Artificial intelligence (AI) represents such a strategic resource, enhancing efficiency, innovation, and performance when effectively deployed (Mikalef et al., 2021; Shrestha et al., 2019). However, its value depends on complementary organizational capabilities, such as flexibility, absorptive capacity, and a data-driven culture, that transform technological assets into enduring advantages (Wamba et al., 2024). In emerging economies, these dynamics are constrained by institutional weaknesses, skill shortages, and financial limitations, which challenge RBV's traditional assumptions (Naidu and Sinha, 2025; Karami et al., 2024). To overcome these limitations, the Dynamic Capabilities Theory (DCT) extends RBV by explaining how firms' sense, seize, and reconfigure resources to adapt in turbulent environments (Teece et al., 1997). These adaptive

processes are particularly relevant for SMEs, which lack slack resources yet must remain agile to survive (Wamba et al., 2021; Li, 2024). Within this framework, entrepreneurial orientation (EO) emerges as a dynamic capability that shapes how AI adoption translates into performance outcomes. By fostering proactiveness, innovation, and risk-taking, EO enhances SMEs' ability to align AI with strategic goals, mobilize resources effectively, and convert adoption into sustained competitiveness (Nayal et al., 2021; Octasylva et al., 2023). Taken together, RBV and DCT provide a complementary theoretical foundation for this study. While RBV highlights the strategic value of AI as a resource, DCT emphasizes the adaptive processes that allow SMEs to realize this value under resource constraints. Integrating the two perspectives enables a richer understanding of how EO moderates the AI-performance relationship, offering a nuanced view of digital transformation in emerging economies.

2. Conceptual Framework and Research Hypotheses

Building on the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT), this study argues that competitive advantage derives less from access to advanced technologies than from the ability to adapt and align them with strategic objectives under uncertainty. Artificial intelligence (AI) is therefore treated as a strategic resource whose benefits depend on firms' internal capacities to deploy and reconfigure it effectively (Dubey et al., 2020). Entrepreneurial orientation (EO), encompassing innovativeness, proactiveness, and risk-taking (Covin and Slevin, 1989), is conceptualized as a dynamic capability that moderates the AI-performance link by enabling firms to sense opportunities, mobilize resources, and respond to environmental turbulence (Octasylva et al., 2023). In Tunisia, where SMEs face financial, technical, and institutional constraints, these theoretical perspectives provide a coherent framework to explain how AI adoption can translate into tangible operational and financial improvements. The integrated model is presented in Figure 1.

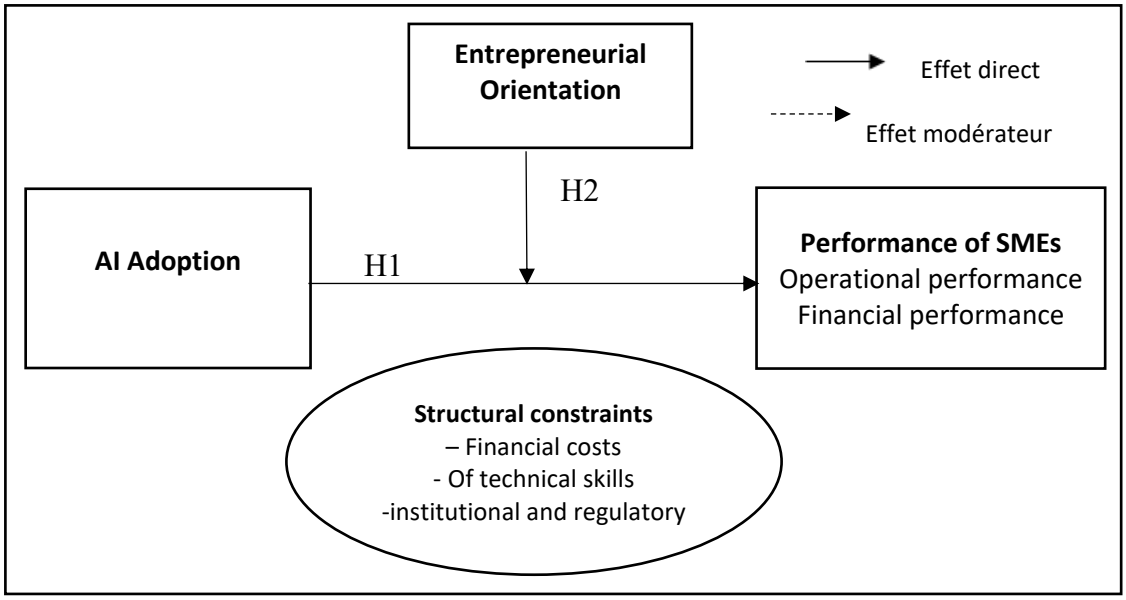

Figure 1: Conceptual model of the AI relationship - performance moderated by entrepreneurial orientation

2.1.AI Adoption and SME Performance

Evidence indicates that AI adoption can enhance SMEs' sustainability and competitiveness by improving efficiency and lowering costs (Soomro et al., 2025). However, these benefits are not automatic, as performance outcomes may be constrained by misalignment with strategic goals, hidden costs, and limited internal capabilities, especially in resource-constrained SMEs (Dwivedi et al., 2021). In this study, performance is assessed as a single construct, reflecting both operational and financial dimensions. This parsimonious approach enables a robust initial test of the model in the context of Tunisian SMEs, while recognizing that future research may refine the analysis by separately examining operational and financial outcomes. Accordingly, we formulate the following hypothesis:

H1. AI adoption positively influences SME performance.

2.2.Entrepreneurial Orientation as a Moderator of the Relationship Between AI Adoption and SME Performance

Entrepreneurial Orientation (EO), defined by innovativeness, proactiveness, and risk-taking (Covin and Slevin, 1989), constitutes a dynamic capability (Teece, 2014) that can shape how firms translate AI adoption into performance outcomes. EO enables SMEs to sense AI-driven opportunities, seize them through proactive resource allocation, and reconfigure internal processes to mitigate implementation risks. Empirical studies confirm this moderating role: Hurby (2024) demonstrates that EO allows firms to overcome structural constraints and extract superior value from digital technologies; Cvijić Čović et al. (2023) highlight its role in fostering routines that

facilitate technology appropriation; and Jang and Lee (2025) show that EO synergizes with absorptive capacity to amplify AI's impact on performance. In this sense, EO operates not only as a strategic posture but also as an organizational mechanism that conditions the extent to which AI adoption generates tangible benefits. As with the first hypothesis, the analysis will focus on the aggregate construct, while the operational (H2a) and financial (H2b) sub-dimensions are reserved for future investigation. Accordingly, we hypothesize that:

H2: Entrepreneurial orientation positively moderates the relationship between AI adoption and SME performance.

3. Methodology

3.1.Methodological Positioning of the Research

This study follows a hypothetico-deductive approach to empirically test a conceptual model based on Dynamic Capabilities Theory (Teece, 2014). It examines how AI adoption influences the performance of Tunisian SMEs and assesses the moderating role of entrepreneurial orientation (EO). Structural constraints, including financial, technical, and regulatory challenges, are incorporated as control variables to better isolate the model's main effects.

3.2.Population, Sampling, and Data Collection

This study adopts a hypothetico-deductive approach, drawing on Dynamic Capabilities Theory (Teece, 2014), to examine the effect of AI adoption on SME performance and the moderating role of entrepreneurial orientation, while controlling for financial, technical, and regulatory constraints. The target population consists of Tunisian SMEs (10–199 employees, APII definition), which constitute a core driver of the national economy yet face specific barriers in adopting AI. A non-probability quota sampling ensured sectoral (industry, services, trade, ICT) and regional (Greater Tunis, Sousse, Sfax) representation. Data were collected between April and May 2025 through a structured questionnaire administered in paper and digital formats to executives, technical leads, and financial managers. A total of 250 valid responses provided the empirical basis for hypothesis testing.

Table 1: Sociodemographic Characteristics of the Sample

Variable	Category	Frequency (n)	Percentage (%)
Region	Greater Tunis	135	54.0%
	Sfax	87	34.8%
	Sousse	28	11.2%
Industry Sector	Services (excluding ICT)	129	51.6%
	Trade	85	34.0%
	Manufacturing	22	8.8%
	ICT / Digital	14	5.6%
Company Size	Fewer than 20 employees	170	68.0%
	Between 20 and 49 employees	48	19.0%
	Between 50 and 199 employees	32	13.0%

An exploratory pre-test was conducted beforehand with a small group of SMEs to ensure the overall clarity of the questionnaire. The technical and conceptual adjustments resulting from this phase are detailed in the following section.

3.3.Data Collection Instrument and Measurement Scales

The study employed a structured questionnaire, adapted from empirically validated scales and pre-tested with ten SME executives to ensure clarity and contextual fit in the Tunisian context. The instrument, written in French, comprised five sections: firm profile, AI adoption, entrepreneurial orientation (EO), performance, and structural constraints. All items were assessed on a five-point Likert scale. AI adoption was measured across technological use, strategic integration, and absorptive capacity; performance through operational and financial indicators; EO through innovativeness, proactiveness, and risk-taking; and financial, technical, and institutional challenges were included as control variables. A detailed list of items and their validated sources (e.g., Qu and Kim, 2025; Xue et al., 2022; Xie et al., 2019) is provided in Appendix A.

3.4.Data Analysis Techniques

Data analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS version 3. This method was selected due to the exploratory nature of the research model, the presence of multidimensional latent variables, and the inclusion of moderating effects. PLS-SEM is particularly suited for studies with moderate sample sizes, aligning with the 250 valid responses analyzed in this research (Hair et al., 2022).

The process followed two stages. First, the measurement model was evaluated based on internal

consistency using Cronbach's alpha and composite reliability, convergent validity through average variance extracted values exceeding 0.50, and discriminant validity using the Fornell–Larcker criterion and HTMT ratios below 0.90. Second, the structural model was assessed through path coefficients, significance levels, and explanatory indicators such as R^2, f^2, and Q^2, in order to test the proposed hypotheses. To evaluate the moderating effect of entrepreneurial orientation, a product indicator approach was applied by creating interaction terms between EO and AI adoption. Structural constraints were included as exogenous control variables, according to PLS-SEM best practices.

4. Results

4.1.Measurement Model Assessment

In line with the methodological guidelines proposed by Hair et al. (2022), the evaluation of the measurement model was conducted in two stages: first, the analysis of internal consistency and convergent validity of the constructs; second, the assessment of discriminant validity among the dimensions.

4.1.1. Internal Consistency and Convergent Validity

Following Hair et al. (2022), the measurement model was evaluated in terms of reliability, convergent validity, and discriminant validity. Internal consistency was confirmed through Cronbach's alpha and composite reliability, both exceeding the 0.70 threshold. Convergent validity was validated by Average Variance Extracted (AVE) values above 0.50, as recommended by Fornell and Larcker (1981). As shown in Table 4.1, all constructs met the required psychometric standards, with Cronbach's alpha ranging from 0.893 to 0.928, composite reliability above 0.91, and AVE values above 0.57. Internal consistency and convergent validity results for all constructs are summarized in the following table:

Table 2. Internal Consistency and Convergent Validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
AI Adoption (AIA)	0.928	0.929	0.940	0.635
Entrepreneurial Orientation (EO)	0.926	0.932	0.938	0.628
SME Performance (SMEP)	0.893	0.897	0.914	0.572
AIA × EO Interaction	1.000	1.000	1.000	1.000
Technical Constraints	1.000	1.000	1.000	1.000
Institutional Constraints	1.000	1.000	1.000	1.000

4.1.2. Discriminant Validity

Discriminant validity was evaluated using the Fornell–Larcker criterion (Fornell and Larcker, 1981). As shown in Table 4.2, for each construct, the square root of the AVE (diagonal values) is greater than its correlations with other constructs (off-diagonal values), confirming discriminant validity. To further validate this result, we also applied the Heterotrait–Monotrait ratio (HTMT; Henseler et al., 2015). All HTMT values fell below the recommended threshold of 0.90, providing additional support for discriminant validity (see Appendix B).

Table 3. Discriminant Validity – Fornell–Larcker Criterion

Construct	AIA	AIA×EO	TConstr	EO	SMEP	Iconstr
AIA	0.797**					
AIA×EO	-0.050	1.000**				
TConstr	0.723	-0.078	1.000**			
EO	0.511	-0.393	0.422	0.792**		
SMEP	0.725	-0.116	0.617	0.659	0.757**	
Iconstr	0.682	-0.138	0.641	0.522	0.632	1.000**

Note: AIA = AI Adoption; EO = Entrepreneurial Orientation; SMEP = SME Performance; TConstr = Technical Constraints; IConstr = Institutional Constraints; AIA×EO = Interaction Term.

In summary, the results indicate that the measurement scales exhibit strong psychometric properties in terms of both reliability and validity, thereby allowing for the evaluation of the structural model.

4.2.Structural Model Results and Hypothesis Testing

4.2.1. Overall Model Quality

The structural model demonstrates strong explanatory power, with $R^2 = 0.660$ for SME performance, meaning that 66% of the variance is explained by AI adoption, entrepreneurial orientation, and their interaction. Predictive relevance is high ($Q^2 = 0.443 > 0.35$) (Hair et al., 2022), and effect size analysis shows substantial contributions from entrepreneurial orientation ($f^2 = 0.264$) and AI adoption ($f^2 = 0.143$), with a smaller but significant interaction effect ($f^2 = 0.017$). Technical ($f^2 = 0.019$) and institutional ($f^2 = 0.016$) constraints contribute modestly. Model fit indices confirm robustness, with SRMR = 0.076 (< 0.08) and NFI = 0.798, both within acceptable thresholds for PLS-SEM with multidimensional constructs. Collectively, these results validate the model's explanatory and predictive strength, supporting hypothesis testing.

4.2.2. Hypothesis Testing

Based on these findings, the hypothesized relationships were tested, and the results of hypothesis testing are presented in the table below:

Table 5. Structural Path Coefficients and Hypothesis Testing Results

Hypothesis	Tested Relationship	Beta (β)	t-value	p-value	Result
H1	AIA → SMEP	0.363	5.774	0.000	Accepted
H2	AIA × EO → SMEP	0.072	2.274	0.023	Accepted

Note: Sub-hypotheses H1a, H1b, H2a, and H2b, related to the operational and financial dimensions of performance, were not tested independently in the retained model. Their empirical examination is reserved for future research.

The results confirm a significant positive effect of AI adoption on the performance of Tunisian SMEs (H1: $\beta = 0.363$, $t = 5.774$, $p = 0.000$), improving both productivity and financial outcomes. Entrepreneurial orientation strengthens this effect through a significant moderating interaction (H2: $\beta = 0.072$, $t = 2.274$, $p = 0.023$), suggesting that firms with greater innovativeness, proactiveness, and risk-taking capture more value from AI technologies. In addition, technical constraints show a small but significant positive effect ($f^2 = 0.019$; $\beta = 0.122$, $t = 2.311$, $p = 0.021$), indicating that some firms transform resource limitations into opportunities for optimization. Institutional barriers, however, remain non-significant ($\beta = 0.111$, $t = 1.953$, $p = 0.051$), suggesting a weaker influence in this context.

5. Discussion of Results

This study investigated the impact of AI adoption on SME performance in Tunisia, with a focus on the moderating role of entrepreneurial orientation (EO) under structural constraints.

5.1.Effects of AI Adoption on SME Performance

The results confirm a significant and positive effect of AI adoption on overall performance ($\beta = 0.363$, $t = 5.774$, $p < 0.001$), validating H1. This effect manifests across both operational and financial dimensions. Operationally, AI enables automation, process optimization, and efficiency gains. For example, chatbots and AI-driven CRM systems enhance customer engagement, while AI-based inventory management reduces costs and strengthens decision-making. Financially, AI adoption contributes to revenue growth and cost savings through predictive analytics and resource-efficient forecasting. These findings are consistent with prior studies highlighting AI's role in enhancing competitiveness and sustainability (Ebuka et al., 2025; Olalekan et al., 2025; Soomro et al., 2025).

Yet, as Dwivedi et al. (2021) caution, such benefits are not automatic. Misalignment with strategic goals, hidden costs, and limited internal capabilities may restrict outcomes, especially in resource-constrained and volatile environments such as Tunisia. This nuance underscores that AI's contribution to performance is conditional on organizational readiness and adaptability. Although operational and financial sub-dimensions were not tested separately, the evidence suggests positive effects across both. Future research should disaggregate these dimensions to clarify how contextual factors and internal capabilities shape the pathways through which AI adoption translates into performance gains.

5.2. Moderating Role of Entrepreneurial Orientation

The results confirm a significant moderating effect of entrepreneurial orientation (EO) on the relationship between AI adoption and SME performance ($\beta = 0.072$; $t = 2.274$; $p = 0.023$), supporting H2. SMEs with stronger EO are better positioned to convert AI adoption into tangible performance gains, though the underlying mechanisms appear context-specific. While earlier studies emphasize structured routines and formalized learning (Sudirman et al., 2025; Cvijić Čović et al., 2023), Tunisian SMEs rely more on pragmatic and informal practices. Entrepreneurially oriented firms often adopt low-cost or open-source AI tools, experiment internally, and mobilize local networks for knowledge exchange. Their risk-taking is reflected in small-scale pilot projects, while proactiveness is evident in resource pooling and the engagement of young graduates to develop tailored digital solutions. These findings reinforce Dynamic Capabilities Theory (Teece, 2014), framing EO as a dynamic capability that allows firms to sense AI-driven opportunities, seize them through flexible strategies, and reconfigure resources to mitigate uncertainty. In this role, EO acts as a catalyst that enhances the appropriation of AI and amplifies its contribution to both productivity and financial performance. Although operational and financial dimensions were not tested separately, the evidence consistently suggests that EO strengthens AI's impact across both, underscoring the strategic importance of entrepreneurial mindsets in resource-constrained environments.

5.2.Role of Control Variables and Contextual Specificities

Although structural constraints were introduced as control variables rather than formal hypotheses, their effects provide meaningful insights. Financial and regulatory barriers showed no significant influence on SME performance, suggesting that these obstacles, while present, are not decisive, particularly for firms compensating through strong entrepreneurial orientation. In contrast, technical constraints exhibited a positive and significant effect ($\beta = 0.122$; $t = 2.311$; $p = 0.021$), a

counterintuitive result explained by the adaptive responses of Tunisian SMEs that, when confronted with infrastructure limitations or skill shortages, accelerate learning, mobilize external expertise, and develop internal digital capabilities. This finding resonates with prior studies highlighting how firms in uncertain environments transform limitations into catalysts for innovation and resilience (Ghobakhloo, 2020; Ransbotham et al., 2022). Consistent with Dynamic Capabilities Theory, it suggests that technical barriers can act as triggers for sensing opportunities, seizing adaptive solutions, and reconfiguring resources, ultimately reinforcing SME performance in resource-constrained contexts.

6. Theoretical and Managerial Implications

This study makes four main theoretical contributions to the literature on digital transformation in SMEs. First, it reinforces the dynamic capabilities theory (Teece, 2014) by showing that AI adoption enhances performance not through mere technology ownership but through the capacity to align, adapt, and deploy it under resource constraints. Second, it positions entrepreneurial orientation (EO) as a dynamic capability that moderates rather than directly drives the AI-performance link. Unlike prior studies that mainly examined EO's direct effect on performance or its mediating role (e.g., Abdulaziz Alhammadi, 2025; Park and Kim, 2025), this research explicitly investigates EO as a moderator, thereby extending DCT to contexts marked by financial, technical, and institutional limitations. Third, by illustrating how Tunisian SMEs rely on pragmatic and frugal practices, such as open-source tools, flexible subscriptions, and informal peer learning, the study shows that capability enactment varies with context, enriching theoretical understanding of adaptive strategies in emerging markets. Finally, the unexpected positive effect of technical constraints reveals that, when coupled with EO, limitations can stimulate learning and resilience, reframing constraints as potential enablers of strategic renewal.

From a managerial perspective, the findings highlight that AI adoption must be approached as a strategic process aligned with internal capabilities rather than as a simple technological upgrade. Effective integration is gradual, tied to productivity and financial objectives, and supported by an entrepreneurial culture that fosters innovation, proactiveness, and calculated risk-taking. Managers should encourage collective learning, inter-firm collaborations, and partnerships adapted to local contexts, while policymakers should facilitate AI diffusion through training, fiscal incentives, and collaborative platforms. Targeting SMEs with strong EO is particularly promising, as they are better positioned to extract value from AI despite external constraints. Moreover, the positive role of technical barriers suggests that managers and policymakers should not only aim to reduce

obstacles but also to reframe them as opportunities for experimentation, capability-building, and innovation.

Conclusion

This research examined the impact of artificial intelligence (AI) adoption on the performance of Tunisian small and medium-sized enterprises (SMEs), with particular attention to the moderating role of entrepreneurial orientation (EO). Grounded in the dynamic capabilities theory, the results confirm that AI operates as a strategic resource capable of improving both productivity and financial outcomes. A key theoretical contribution lies in providing the first empirical evidence that EO explicitly moderates the AI-performance relationship in resource-constrained contexts. By fostering adaptation, experimentation, and proactive learning, EO enables SMEs to strategically leverage AI despite financial, technical, and institutional obstacles. The analysis further revealed an unexpected positive effect of technical constraints on performance. This counterintuitive result suggests that SMEs aware of their limitations tend to adopt adaptive strategies, such as internal upskilling, external partnerships, or collective learning, that transform barriers into sources of innovation and growth. Such evidence invites a reconsideration of how constraints are conceptualized in the literature on digital transformation.

From a managerial standpoint, the findings stress that AI adoption should not be viewed as a simple technological investment but rather as a strategic process requiring alignment with entrepreneurial posture and internal capabilities. They also emphasize the role of policymakers in creating enabling conditions, through targeted training, incentives, and collaborative platforms, that allow SMEs to exploit AI more effectively. Despite these contributions, the study has several limitations. Its focus on Tunisia may restrict generalizability, and its cross-sectional design prevents capturing the long-term dynamics of AI adoption. In addition, reliance on self-reported survey data raises the possibility of common method bias, despite measures taken to reduce it. Future research should therefore adopt longitudinal and multi-source designs, extend the analysis to cross-country settings, and investigate complementary internal capabilities, such as digital agility or organizational learning, to deepen understanding of AI-driven performance outcomes. In sum, this study extends both the resource-based view and the dynamic capabilities theory to constrained environments, demonstrating how EO transforms AI from a mere technological input into a performance-enhancing strategic asset.

References

Abdul Wahab, M. D., and Radmehr, M. (2024). The impact of AI assimilation on firm performance in small and medium-sized enterprises: A moderated multi-mediation model. *Journal of Business Research*, *174*, 114500. org/10.1016/j.heliyon.2024.e29580

Abebe, M. A. (2014). Electronic commerce adoption, entrepreneurial orientation and small- and medium-sized enterprise (SME) performance. *Journal of Small Business and Enterprise Development*, *21*(1), 100-116. https://doi.org/10.1108/JSBED-10-2013-0145

Alhammadi, A. (2025). Measuring the antecedents of employees' intention to use artificial intelligence in the manufacturing sector. *Problems and Perspectives in Management*, 23(1), 557–568. http://dx.doi.org/10.21511/ppm.23(1).2025.42

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

Assidi, S., Omran, M., Rana, T., & Borgi, H. (2025). The role of AI adoption in transforming the accounting profession: A diffusion of innovations theory approach. *Journal of Accounting & Organizational Change.* Advance online publication. https://doi.org/10.1108/JAOC-04-2024-0124

Ayinaddis, S. G. (2025). Artificial intelligence adoption dynamics and knowledge in SMEs and large firms: A systematic review and bibliometric analysis. *Journal of Innovation & Knowledge*, 10, 100682. https://doi.org/10.1007/s13132-024-01876-2

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. *Journal of Business Research, 132,* 85–97. https://doi.org/10.1016/j.indmarman.2021.09.003

Badghish, S., and 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

Brynjolfsson, E., Li, D., and Raymond, L. R. (2023). Generative AI at Work (No. w31161). *National Bureau of Economic Research*. doi:10.1001/jama.2023.25054

Cherla, S., and Sharma, R. (2024). Enhancing Operational Performance: The Role of Entrepreneurial Orientation, Big Data Analytics, and AI Under Environmental Dynamis. *Researcher Academy Innovation Data Analysis*, (3), 140-252. https://doi.org/10.69725/raida.v1i3.170

Covin, J. G., and Slevin, D. P. (1989). Strategic management of small firms in hostile and benign environments. *Strategic Management Journal*, 10, 75–87.

DeStefano, T. J., Teodorovicz, T., Cho, J., Kim, H., & Paik, J. (2022, août). What determines AI adoption? *Proceedings of the Eighty-second Annual Meeting of the Academy of Management. Academy of Management.* https://doi.org/10.5465/AMBPP.2022.14791

Dell'Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., and Lakhani, K. R. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality (Harvard Business School Technology & Operations Mgt. Unit Working Paper No. 24-013). *Harvard Business School*. http://dx.doi.org/10.2139/ssrn.4573321

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Roubaud, D., and Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics, 226,* 107610.

Dwivedi, Y. K., et al. (2021). The role of organizational readiness in AI adoption. *International Journal of Information Management*, 57, Article 102349.

Eisenhardt, K. M., and Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, 21(10–11), 1105–1121.

Fang, G., Qalati, S. A., Ostic, D., Shah, S. M. M., and Mirani, M. (2021). Effects of entrepreneurial orientation, social media, and innovation capabilities on SME performance in emerging countries: a mediated–moderated model. *Technology Analysis and Strategic Management*, *34*(9), 1056–1070. https://doi.org/10.1080/09537325.2021.1957816

Fernández-Mesa, A., Alegre, J., and Chiva, R. (2014). Organizational learning capability and innovation performance: A bibliometric and meta-analytic integration. *International Journal of Management Reviews*, 16(4), 397–417.

Furr, N. R., and Eisenhardt, K. (2021). Strategy and uncertainty: Resource-based view, strategy-creation view, and the hybrid between them. *Journal of Management*,

Ghobakhloo, M., and Ching Tang, S. H. (2019). Barriers to Industry 4.0 adoption in SMEs: Empirical evidence. *Journal of Manufacturing Technology Management*, 31(3), 451–476.

Gouveia, S., de la Iglesia, D. H., Abrantes, J. L., and López Rivero, A. J. (2024). Transforming strategy and value creation through digitalization? *Administrative Sciences*, Published November 20, 2024.

Haenlein, M., and Kaplan, A. (2019). Siri, Siri in my hand: Who's the smartest in the land? On the

interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1), 15–25.

Hrubý, V. (2024). Exploring AI Adoption Dynamics and Entrepreneurial Orientation in Czech Chemical SMEs: A Pilot Study Perspective. *Scientific Papers of the University of Pardubice, Series D: Faculty of Economics and Administration*.

Jang, Y., and Lee, K. (2025). Digital Entrepreneurial Orientation, Technology Absorptive Capacity, and Digital Innovation on Business Performance. *Systems 2025, 13, 300*.

Jankovic, S. D., and Curovic, D. M. (2023). Strategic Integration of Artificial Intelligence for Sustainable Businesses: Implications for Data Management and Human User Engagement in the Digital Era. *Sustainability, 15*(21), 15208.

Karami, M., Hossain, M., Ojala, A., and Mehrara, N. (2024). Resource mobilization and technology adoption by small firms to co-create opportunities in uncertain environments. *Journal of Research in Marketing and Entrepreneurship*.

Kukreja, A. (2025). AI adoption in SMEs: Integrating supply chain and financial strategies for competitive advantage. *International Journal for Multidisciplinary Research, 7*(1), 45–56. https://doi.org/10.36948/ijfmr.2025.v07i01.35821

Kraus, S., et al. (2018). Entrepreneurial orientation and technological innovation in SMEs. *Journal of Business Research*, 88, 259–269.

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.

Maycotte, S., Alvarez-Risco, A., Garcia-Valenzuela, E., and Kuljis, M. (2025). Digital capabilities in emerging market firms: Construct development, scale validation, and implications for SMEs. *Journal of Open Innovation: Technology, Market, and Complexity, 11*(10), 100513.

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

Miller, D. (1983). The correlates of entrepreneurship in three types of firms. *Management Science*, *29*(7), 770-791.

Naidu, A., and Sinha, M. (2025). Revisiting firm resources that drive international performance—evidence from India. *Review of International Business and Strategy*. Advance online publication.

Nasution, M.D.T.P., Rafiki, A., Lubis, A. and Rossanty, Y. (2021), "Entrepreneurial orientation, knowledge management, dynamic capabilities towards e-commerce adoption of SMEs in Indonesia". *Journal of Science and Technology Policy Management*, Vol. 12 No. 2, pp. 256-282.

Octasylva, A. R. P., Yuliati, L. N., and Hartoyo, H. (2023). Entrepreneur orientation and social capital as a key to developing dynamic capability: A conceptual framework. *Indonesian Journal of Business and Entrepreneurship*, *9*(2), 123-134.

Olalekan, O. O. (2025). The role of AI in optimizing decision-making for small and medium enterprises (SMEs) in Nigeria's retail industry. *International Journal of Management & Entrepreneurship Research*, 7(4), 328–340.

Park, D.-H., Jiang, Q., and Kim, K. H. (2025). Impact of the expected B2B internal customer experience on intention to adopt artificial intelligence (AI). *Journal of Global Scholars of Marketing Science.* Advance online publication.

Qu, C., and Kim, E. (2025). Investigating AI adoption, knowledge absorptive capacity, and open innovation in Chinese apparel MSMEs: An extended TAM-TOE model with PLS-SEM analysis. *Sustainability, 17*(5), 1873. **https://doi.org/10.3390/su17051873**

Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain, B., and Kiron, D. (2022). The cultural benefits of artificial intelligence in the enterprise. *MIT Sloan Management Review*, *63*(4), 31-36.

Segarra-Blasco, A., Tomàs-Porres, J., and Teruel, M. (2025). AI, robots and innovation in European SMEs. *Small Business Economics, 65(1), 719–745.*

Sharma, V. (2024). The integration of AI and RPA in financial services: Enhancing fraud prevention and operational efficiency. *International Journal of Multidisciplinary Research and Growth Evaluation, 5*(1), 171–176.

Shrestha, Y. R., Ben-Menahem, S. M., and von Wangenheim, F. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review, 61*(4), 66–83.

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.

Teece, D. J. (2014). A dynamic capabilities-based entrepreneurial theory of the multinational enterprise. *Journal of International Business Studies*, *45*(1), 8–37.

Upadhyay, N., et al. (2022). The influence of digital entrepreneurship and entrepreneurial orientation on intention of family businesses to adopt artificial intelligence: examining the mediating role of business innovativeness. *International Journal of Entrepreneurial Behavior*.

Vrontis, D., Chaudhuri, R., & Chatterjee, S. (2022). Adoption of digital technologies by SMEs for sustainability and value creation: Moderating role of entrepreneurial orientation. *Sustainability,*

14(13), 7949.

Wamba-Taguimdje, S.-L., Wamba, S. F., Kala Kamdjoug, J. R., and 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.

Wamba-Taguimdje et al. (2021), "Institutional Barriers to AI Implementation in African SMEs", Technological Forecasting and Social Change

Xie, X., Hoang, T. T., and Zhu, Q. (2022). Green process innovation and financial performance: The role of green social capital and customers' tacit green needs. *Journal of Innovation & Knowledge, 7*(1), 100165. https://doi.org/10.1016/j.jik.2022.100165

Xue, M., Boadu, F., and Xie, Y. (2019). The penetration of green innovation on firm performance: Effects of absorptive capacity and managerial environmental concern. *Sustainability, doi:10.3390/su11092455 11*(9), 2455.

Yin, L., Zhu, S., and Zhou, J. (2023). AI technology adoption, AI knowledge integration and AI product development performance. *Service Science*, Chapitre 25, pp.

Yusuf, S. O., Durodola, R. L., Ocran, G., Abubakar, J. E., Echere, A. Z., and Paul-Adeleye, A. H. (2024). Challenges and opportunities in AI and digital transformation for SMEs: A cross-continental perspective. *World Journal of Advanced Research and Reviews, 23*(3), 668–678.

Zebec, A., and Indihar Štemberger, M. (2020). Conceptualizing a capability-based view of artificial intelligence adoption in a BPM context. In A. del-Río-Ortega, H. Leopold, and F. M. Santoro (Eds.), Business Process Management Workshops: *BPM 2020 International Workshops, Revised Selected Papers*, vol. 397, pp. 194–205). Springer. https://doi.org/10.1007/978-3-030-66498-5_15

Books references

Russell, S., and Norvig, P. (2020). Artificial intelligence: A modern approach (4th ed.). *Pearson*.

Web Source references

Banque Centrale de Tunisie. (2023). Annual Report on Inflation and Tunisia's Macroeconomic Situation. Tunis: BCT. https://www.bct.gov.tn/bct/siteprod/index.jsp

World Bank. (2022). Tunisia Digital Economy Assessment Report. Washington, D.C.: World Bank. https://www.worldbank.org/en/country/tunisia/overview

GSMA. (2023). State of the Industry Report*: Mobile for Development – Africa*. London: GSMA. https://www.gsma.com/sotir/wp-content/uploads/2025/04/GSMA-SOTIR-2023.pdf

INS (Institut National de la Statistique). (2023). Statistics on SMEs in Tunisia. Tunis: INS. UTICA. (2023). Report on Tunisian Entrepreneurship and Structural Constraints. Tunis: UTICA. https://www.ins.tn/en