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When Does AI Adoption Enhance SME Innovation Performance? The Roles of Absorptive Capacity, Entrepreneurial Agility, and Digital Maturity

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Abstract

Artificial intelligence (AI) adoption is increasingly viewed as a driver of innovation in small and medium-sized enterprises (SMEs). Yet adopting AI tools does not necessarily mean that firms can convert them into innovation outcomes. Drawing on dynamic capabilities theory and absorptive capacity theory, this study examines when and how AI adoption intensity enhances SME innovation performance. We propose a capability-building model in which AI adoption intensity strengthens absorptive capacity, absorptive capacity enhances entrepreneurial agility, and entrepreneurial agility improves innovation performance. We further examine digital maturity as a boundary condition that strengthens the AI adoption–absorptive capacity relationship and the downstream indirect pathway to innovation performance. The model was tested using survey data from 294 SMEs operating in an emerging economy context and partial least squares structural equation modeling. The results show that AI adoption intensity positively affects absorptive capacity, absorptive capacity strongly enhances entrepreneurial agility, and entrepreneurial agility improves SME innovation performance. However, the direct effect of AI adoption intensity on innovation performance is not significant, whereas the total and serial indirect effects are significant, indicating an indirect-only mediation mechanism. The findings also show that digital maturity positively moderates the relationship between AI adoption intensity and absorptive capacity and strengthens the serial indirect effect through absorptive capacity and entrepreneurial agility. PLSpredict results further indicate satisfactory indicator-level predictive relevance for SME innovation performance. The study contributes to AI innovation research by showing that AI adoption becomes innovation-enhancing not through adoption alone, but through absorptive capacity, entrepreneurial agility, and digital maturity.

JEL Classification: L26; M13; O32; O33; L25

Highlights

• AI adoption does not directly enhance SME innovation performance.

• AI adoption improves innovation through absorptive capacity and entrepreneurial agility.

• Digital maturity strengthens the AI adoption–absorptive capacity relationship.

• The study supports a serial moderated mediation mechanism.

• Evidence is based on 294 SMEs in an emerging economy context using PLS-SEM.

1. Introduction

Artificial intelligence (AI) is rapidly becoming one of the most consequential technological forces shaping contemporary entrepreneurship, innovation, and firm competitiveness. Recent advances in machine learning, analytics, automation, and generative AI have made AI-based tools more accessible to firms of different sizes and across a wide range of industries. For small and medium-sized enterprises

(SMEs), this development is particularly important. AI can support opportunity recognition, customer and market analysis, product and service development, process automation, decision support, and business model experimentation. Yet the growing availability of AI tools does not mean that firms automatically convert AI adoption into innovation outcomes.

This distinction is central to the present study. The current managerial and policy debate has moved beyond whether firms can access AI tools; the more important question is whether firms can transform AI use into innovation-relevant capabilities and performance outcomes. Recent survey evidence suggests that AI adoption is expanding quickly, but value capture remains uneven (Stanford Institute for Human-Centered Artificial Intelligence, 2025). For example, evidence from European firms indicates that while reported AI use is becoming widespread, intensive use remains much less common. Similarly, recent evidence from mid-sized firms suggests that generative AI adoption may grow faster than measurable productivity or efficiency gains. This pattern reflects a broader “adoption–value gap”: firms may adopt AI, but many still struggle to translate AI-enabled insights into organizational learning, entrepreneurial action, and innovation performance.

The adoption–value gap is especially relevant for SMEs. SMEs are widely recognized as central actors in employment, entrepreneurship, local economic development, and innovation. In this study, SMEs are understood as firms that fall below the standard size thresholds for large enterprises; consistent with the European Commission definition (European Commission, 2003), SMEs are typically firms with fewer than 250 employees and with turnover or balance-sheet thresholds below the limits specified for medium-sized enterprises. This definition includes micro, small, and medium-sized firms and is appropriate for studying firms that differ from large corporations in terms of resource endowments, managerial structure, digital infrastructure, and innovation routines.

SMEs occupy a paradoxical position in the AI transformation. On the one hand, they may benefit from agility, proximity to customers, informal decision-making, and faster experimentation. These characteristics can make SMEs well positioned to use AI for market sensing, rapid adaptation, and opportunity-driven innovation. On the other hand, SMEs often face constraints in financial resources, specialized digital skills, data readiness, formalized innovation processes, and managerial capacity. As a result, they may adopt AI tools without developing the organizational capabilities required to make AI strategically useful. This makes SMEs a theoretically and practically important context for studying when AI adoption enhances innovation. Empirically, this study focuses on SMEs in an emerging economy context, where the innovation value of AI adoption is likely to depend strongly on complementary capabilities such as absorptive capacity, entrepreneurial agility, and digital maturity.

Prior research has provided valuable insights into AI capability, AI-enabled business value, and the role of AI in innovation management. AI capability research suggests that AI can enhance creativity, decision-making, and performance when firms possess complementary organizational resources and capabilities (Mikalef & Gupta, 2021). Studies on AI and business value similarly emphasize that AI creates value through organizational mechanisms rather than through technical deployment alone (Enholm et al.,

2022). Innovation management research also shows that AI can support different stages of the innovation process, including search, idea generation, development, and implementation (Haefner et al., 2021). However, despite these contributions, three gaps remain.

First, much of the existing discussion still treats AI adoption or AI capability as a relatively direct antecedent of innovation or firm performance. This direct-effect logic is useful but incomplete. AI adoption may generate data, predictions, and recommendations, but these outputs must be interpreted, integrated, and acted upon before they can become innovation outcomes. Second, the SME context remains underdeveloped in AI and innovation research. Large firms often possess more formal data infrastructures, specialized AI teams, and structured innovation systems, while SMEs rely more heavily on managerial cognition, flexible routines, and entrepreneurial action. Therefore, mechanisms derived from large-firm AI adoption may not fully explain how AI creates innovation value in SMEs. Third, the literature has not sufficiently explained the boundary conditions under which AI adoption becomes capability-enhancing. In particular, digital maturity may determine whether SMEs can convert AI use into knowledge absorption and innovation-relevant action.

To address these gaps, this study develops and tests a capability-based model of AI-enabled SME innovation. Drawing on dynamic capabilities theory (Teece et al., 1997; Teece, 2007) and absorptive capacity theory (Cohen & Levinthal, 1990; Zahra & George, 2002), the study argues that AI adoption intensity does not automatically enhance SME innovation performance. Instead, AI adoption becomes valuable through a sequential capability-building mechanism. First, AI adoption intensity strengthens absorptive capacity by improving the firm's ability to identify, acquire, assimilate, transform, and exploit relevant knowledge. Second, absorptive capacity enhances entrepreneurial agility by enabling the firm to recognize opportunities, respond rapidly to market changes, experiment with new ideas, and reconfigure resources under uncertainty. Third, entrepreneurial agility translates AI-enabled and absorbed knowledge into SME innovation performance.

The study also argues that digital maturity serves as a key boundary condition. Digital maturity reflects the extent to which SMEs possess the digital infrastructure, integrated tools, data readiness, employee digital skills, digital culture, managerial support, and investment orientation required to use advanced digital technologies effectively. The digital transformation literature has consistently emphasized that technology-driven value creation depends not only on adopting digital technologies, but also on organizational readiness, managerial commitment, processes, data, and capabilities (Vial, 2019; Warner & Wäger, 2019; Verhoef et al., 2021). Accordingly, the present study proposes that digital maturity strengthens the relationship between AI adoption intensity and absorptive capacity. In digitally mature SMEs, AI-generated insights are more likely to be accessible, interpretable, shareable, and actionable. In less digitally mature SMEs, AI tools may remain fragmented, experimental, or disconnected from organizational learning routines.

This study therefore asks: when does AI adoption enhance SME innovation performance? To answer this question, the study examines the roles of absorptive capacity, entrepreneurial agility, and digital maturity

in the relationship between AI adoption intensity and SME innovation performance. The empirical model is tested using survey data from 294 SMEs operating in Iran, an emerging economy context, that had adopted or experimented with AI-based tools. Partial least squares structural equation modeling is used to assess the measurement model, structural relationships, mediation effects, moderation effect, and out-of-sample predictive relevance.

The study makes four contributions. First, it contributes to AI and innovation research by shifting the focus from AI adoption as a direct predictor of innovation to AI adoption as an input into a capability-building process. This helps explain why AI adoption may not produce innovation outcomes unless firms develop complementary knowledge and entrepreneurial capabilities. Second, it contributes to SME innovation research by showing how SMEs can convert AI-enabled insights into innovation performance despite resource constraints. Third, it contributes to entrepreneurship research by positioning entrepreneurial agility as the action-oriented mechanism through which absorbed knowledge becomes innovation. Fourth, it contributes to digital transformation research by identifying digital maturity as a boundary condition that strengthens the AI adoption–absorptive capacity relationship and the downstream indirect pathway to innovation performance.

The remainder of the article is organized as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 explains the research methodology, measurement instrument, sampling procedure, and data analysis approach. Section 4 presents the empirical results, including measurement model assessment, structural model analysis, mediation and moderation tests, and PLSpredict results. Section 5 discusses the findings, theoretical contributions, practical implications, limitations, and future research directions.

2. Literature Review and Hypotheses Development

Artificial intelligence (AI) is increasingly viewed as a general-purpose and capability-enhancing technology that can reshape how firms process information, recognize opportunities, support decisions, and develop innovations. Unlike traditional digital tools that mainly support automation or communication, AI-based tools can assist firms in prediction, pattern recognition, market sensing, customer analysis, process improvement, and knowledge recombination. However, the innovation value of AI is not automatic. Prior research on general-purpose technologies suggests that the benefits of advanced technologies depend heavily on complementary intangible investments, organizational learning, managerial routines, and capability development (Brynjolfsson et al., 2021). Similarly, research on AI and management emphasizes that AI creates value through the interaction between automation, augmentation, human expertise, and organizational adaptation rather than through technology adoption alone (Raisch & Krakowski, 2021).

This argument is particularly relevant for small and medium-sized enterprises (SMEs). SMEs often face stronger resource constraints, lower formalization, limited data infrastructure, fewer specialized digital skills, and greater dependence on owner-manager decision-making than large firms. At the same time,

SMEs may benefit from flexibility, proximity to customers, rapid decision-making, and entrepreneurial responsiveness. Therefore, AI adoption may provide SMEs with new opportunities for innovation, but these opportunities are likely to be realized only when AI-generated insights are absorbed, interpreted, and converted into agile entrepreneurial action.

The present study draws primarily on dynamic capabilities theory and absorptive capacity theory. Dynamic capabilities theory explains how firms sense opportunities, seize them, and reconfigure resources in changing environments (Teece et al., 1997; Teece, 2007). This perspective is useful for explaining why AI adoption may enhance innovation only when firms develop complementary capabilities. Absorptive capacity theory explains how firms recognize the value of external knowledge, assimilate it, and apply it commercially (Cohen & Levinthal, 1990). Zahra and George (2002) further conceptualize absorptive capacity as a dynamic capability consisting of acquisition, assimilation, transformation, and exploitation. Combining these perspectives, this study argues that AI adoption enhances SME innovation performance through a sequential capability-building mechanism: AI adoption intensity strengthens absorptive capacity, absorptive capacity enhances entrepreneurial agility, and entrepreneurial agility ultimately improves innovation performance.

This logic is consistent with recent AI capability research. Mikalef and Gupta (2021) show that AI capability can support organizational creativity and performance, but their work also suggests that AI value depends on organizational resources and capabilities. Enholm et al. (2022) similarly argue that AI-enabled business value emerges through organizational mechanisms rather than through technical adoption alone. In innovation management, Haefner et al. (2021) emphasize that AI can support different stages of the innovation process, but also highlight the need to understand the organizational conditions and capabilities through which AI contributes to innovation. Accordingly, this study shifts the question from whether AI adoption matters to when and through which capability pathways AI adoption enhances SME innovation.

2.1. AI Adoption Intensity and Absorptive Capacity

AI adoption intensity refers to the extent to which SMEs use AI-based tools across actual business activities, including decision-making, market analysis, product or service development, process improvement, opportunity identification, and strategic or operational decision support. This conceptualization goes beyond general AI awareness or intention to adopt AI. It captures the functional scope and depth of AI use in managerial and innovation-related activities.

The relationship between AI adoption and absorptive capacity can be explained through the information-processing and knowledge-based roles of AI. AI-based tools can help firms scan markets, identify customer patterns, analyze external data, detect emerging trends, and generate new insights. These functions can strengthen the firm’s ability to acquire and interpret external knowledge. However, the knowledge value of AI depends on whether the firm can connect AI-generated insights with existing

knowledge, routines, and strategic priorities. In this sense, AI adoption can act as an input to absorptive capacity by expanding the volume, variety, and analytical quality of knowledge available to the firm.

Absorptive capacity has long been considered central to learning and innovation (Cohen & Levinthal, 1990). Firms with stronger absorptive capacity are better able to recognize valuable external knowledge, assimilate it, transform it, and exploit it for commercial purposes (Zahra & George, 2002; Flatten et al., 2011). In the AI context, this suggests that SMEs using AI more intensively should become better at identifying relevant knowledge, interpreting technological and market signals, and transforming insights into practical applications. Therefore, AI adoption intensity is expected to enhance absorptive capacity.

H1. AI adoption intensity has a positive effect on absorptive capacity in SMEs.

2.2. Absorptive Capacity and Entrepreneurial Agility

Entrepreneurial agility refers to the firm's ability to rapidly recognize opportunities, respond to changes in customer needs, experiment with new ideas, reallocate resources, and make entrepreneurial decisions under uncertainty. While organizational agility has traditionally been associated with responsiveness and operational adjustment, entrepreneurial agility emphasizes opportunity-oriented action and flexible resource mobilization in uncertain environments.

Absorptive capacity provides the knowledge foundation for entrepreneurial agility. Firms that are better at acquiring and assimilating external knowledge are more likely to detect changes in customer needs, understand technological shifts, identify emerging opportunities, and respond before competitors. Zahra and George (2002) conceptualize absorptive capacity as a dynamic capability because it enables firms to transform and exploit knowledge in changing environments. From this perspective, absorptive capacity is not only a learning capability but also a basis for strategic and entrepreneurial action.

The information systems literature also supports the link between knowledge-processing capabilities and agility. Sambamurthy et al. (2003) argue that digital options can shape organizational agility by enhancing reach, richness, and flexibility. Lu and Ramamurthy (2011) distinguish between market-capitalizing agility and operational-adjustment agility, showing that IT-enabled capabilities can help firms respond to market opportunities and operational changes. In digitally disrupted environments, Karimi and Walter (2015) show that dynamic capabilities contribute to entrepreneurial agility and firm response. Applying this logic to SMEs, firms with stronger absorptive capacity should be better able to translate new knowledge into rapid entrepreneurial responses.

H2. Absorptive capacity has a positive effect on entrepreneurial agility in SMEs.

2.3. Entrepreneurial Agility and SME Innovation Performance

SME innovation performance refers to the extent to which firms introduce new or significantly improved products, services, processes, customer-related methods, or business models and convert new ideas

into marketable offerings. Innovation in SMEs is often less formalized than in large firms and may occur through incremental experimentation, customer-driven adaptation, rapid product/service improvement, process redesign, or business model renewal.

Entrepreneurial agility is expected to enhance SME innovation performance because innovation requires not only knowledge but also timely action. Agile SMEs are better positioned to respond to customer feedback, experiment with new ideas, adjust offerings, reconfigure resources, and commercialize opportunities. This is especially important in AI-enabled contexts, where firms may receive more data and insights but still need organizational speed and entrepreneurial judgment to act on them.

Prior innovation research shows that product, process, marketing, and organizational innovations are closely linked to firm performance (Gunday et al., 2011), while organizational innovativeness reflects the firm's capacity to introduce and implement new ideas (Wang & Ahmed, 2004). Digital entrepreneurship research also emphasizes that digital technologies change the nature of opportunity creation, experimentation, and value generation (Nambisan, 2017; Nambisan et al., 2019). Therefore, entrepreneurial agility should function as a key action capability through which SMEs convert opportunities and knowledge into innovation outcomes.

H3. Entrepreneurial agility has a positive effect on SME innovation performance.

2.4. Direct Effects of AI Adoption Intensity and Absorptive Capacity

Although the central argument of this study is capability-based and indirect, the model also specifies direct paths to provide a rigorous test of the proposed mechanism. First, AI adoption intensity may directly enhance entrepreneurial agility. AI-based tools can support faster information processing, opportunity identification, and decision support. By improving the speed and quality of information available to managers, AI adoption may help SMEs recognize market changes and respond more quickly. However, this relationship is expected to be weaker than the indirect pathway through absorptive capacity because AI-generated insights must still be interpreted and embedded in firm knowledge routines.

H4. AI adoption intensity has a positive effect on entrepreneurial agility in SMEs.

Second, absorptive capacity may directly improve SME innovation performance. Firms that can acquire, assimilate, transform, and exploit knowledge are more likely to generate new products, improve processes, and commercialize ideas. The relationship between absorptive capacity and innovation has been widely emphasized in the innovation and knowledge management literature (Cohen & Levinthal, 1990; Zahra & George, 2002). Therefore, absorptive capacity is expected to have a direct positive effect on innovation performance, in addition to its indirect effect through entrepreneurial agility.

H5. Absorptive capacity has a positive effect on SME innovation performance.

Third, AI adoption intensity may have a direct positive association with SME innovation performance. AI can support product/service development, customer analytics, process automation, and business model experimentation. Prior AI and innovation research suggests that AI can support different stages of innovation management, from idea generation and search to development and implementation (Haefner et al., 2021). Nevertheless, the broader technology and AI capability literature indicates that AI's innovation benefits are likely to depend on complementary capabilities and organizational readiness (Brynjolfsson et al., 2021; Mikalef & Gupta, 2021; Enholm et al., 2022). Therefore, the direct relationship is included as a baseline effect, while the study expects the indirect capability-building pathway to provide the main explanation.

H6. AI adoption intensity has a positive effect on SME innovation performance.

2.5. The Mediating Role of Absorptive Capacity

The first mediation mechanism concerns the role of absorptive capacity in the relationship between AI adoption intensity and entrepreneurial agility. AI adoption can expand the firm's access to market signals, customer insights, operational data, and technological information. However, access to AI-generated information does not automatically create entrepreneurial action. Firms need absorptive capacity to interpret, combine, and apply these insights.

Absorptive capacity therefore serves as a bridge between AI adoption and entrepreneurial agility. AI adoption provides new data and analytical possibilities; absorptive capacity enables the firm to turn those possibilities into usable knowledge; and this knowledge then supports opportunity recognition and agile entrepreneurial response. This logic is consistent with dynamic capabilities theory, which emphasizes that sensing and seizing opportunities depend on the firm's ability to process and reconfigure knowledge (Teece, 2007). It is also consistent with absorptive capacity theory, which views knowledge acquisition, assimilation, transformation, and exploitation as central to innovation and adaptation.

H7. Absorptive capacity mediates the relationship between AI adoption intensity and entrepreneurial agility.

2.6. The Mediating Role of Entrepreneurial Agility

The second mediation mechanism concerns the role of entrepreneurial agility in the relationship between absorptive capacity and SME innovation performance. Absorptive capacity enables firms to understand and apply new knowledge, but knowledge alone may not be sufficient to produce innovation. To generate innovation outcomes, firms must act on knowledge by experimenting, reallocating resources, adjusting offerings, and pursuing emerging opportunities.

Entrepreneurial agility captures this action-oriented conversion process. In SMEs, innovation often depends on rapid decision-making, flexible resource use, close customer interaction, and willingness to experiment. Therefore, absorptive capacity should improve innovation performance partly because it

strengthens entrepreneurial agility. Firms that absorb knowledge effectively become better able to recognize and act on innovation opportunities.

H8. Entrepreneurial agility mediates the relationship between absorptive capacity and SME innovation performance.

2.7. Serial Mediation of Absorptive Capacity and Entrepreneurial Agility

The central mechanism proposed in this study is a serial mediation pathway from AI adoption intensity to SME innovation performance through absorptive capacity and entrepreneurial agility. This mechanism explains why AI adoption may not directly or automatically produce innovation outcomes. AI adoption first enhances the firm's ability to access and process knowledge. Absorptive capacity then enables the firm to assimilate and transform this knowledge. Entrepreneurial agility subsequently converts absorbed knowledge into rapid experimentation, opportunity pursuit, resource reconfiguration, and innovation outcomes.

This sequential logic integrates the knowledge-based and dynamic capability perspectives. Absorptive capacity represents the knowledge-processing capability, while entrepreneurial agility represents the opportunity-action capability. AI adoption intensity provides the technological input, but innovation performance emerges when this input is translated into knowledge absorption and entrepreneurial action. This argument is particularly relevant for SMEs because they often lack large-scale R&D structures and must rely on flexible, capability-based mechanisms to benefit from AI.

H9. Absorptive capacity and entrepreneurial agility sequentially mediate the relationship between AI adoption intensity and SME innovation performance.

2.8. Digital Maturity as a Boundary Condition

Digital maturity refers to the extent to which a firm possesses the digital infrastructure, integrated tools, data readiness, digital skills, digital culture, managerial support, and investment orientation required to use advanced technologies effectively. In AI-enabled contexts, digital maturity is especially important because AI adoption depends not only on access to AI tools but also on the firm's ability to provide usable data, integrate digital systems, develop employee skills, and support technology-enabled decision-making.

The digital transformation literature emphasizes that digital value creation depends on organizational and managerial transformation, not only on technology adoption (Vial, 2019; Verhoef et al., 2021). Warner and Wäger (2019) argue that digital transformation requires dynamic capabilities for sensing, seizing, and transforming. SME digitalization research similarly suggests that digital tools create value when firms possess complementary digital resources, managerial commitment, skills, and organizational readiness (Li et al., 2018; Eller et al., 2020). Therefore, digital maturity should strengthen the relationship between AI adoption intensity and absorptive capacity.

In SMEs with high digital maturity, AI-generated insights are more likely to be accessible, interpretable, shareable, and actionable. These firms typically have better digital infrastructure, more reliable data, stronger digital skills, and a culture more supportive of digital transformation. As a result, AI adoption is more likely to enhance knowledge acquisition, assimilation, transformation, and exploitation. In contrast, SMEs with low digital maturity may adopt AI tools but struggle to convert them into absorptive capacity due to fragmented data, weak digital skills, poor integration, or limited managerial support.

H10. Digital maturity positively moderates the relationship between AI adoption intensity and absorptive capacity, such that the relationship is stronger when digital maturity is high.

Because the proposed model is sequential, the moderating role of digital maturity is also expected to influence the downstream indirect pathway. If digital maturity strengthens the link between AI adoption intensity and absorptive capacity, then it should also strengthen the indirect effect of AI adoption intensity on entrepreneurial agility and innovation performance through absorptive capacity and entrepreneurial agility. This conditional process logic implies that AI adoption produces stronger innovation-related capability effects when SMEs are digitally mature.

H11. Digital maturity strengthens the indirect effect of AI adoption intensity on SME innovation performance through absorptive capacity and entrepreneurial agility.

2.9. Conceptual Model

The conceptual model integrates AI adoption intensity, absorptive capacity, entrepreneurial agility, digital maturity, and SME innovation performance. AI adoption intensity is proposed to enhance absorptive capacity, which in turn strengthens entrepreneurial agility and ultimately improves SME innovation performance. The model also includes direct paths from AI adoption intensity to entrepreneurial agility and SME innovation performance, as well as from absorptive capacity to SME innovation performance, to allow a rigorous assessment of whether the effect of AI adoption is direct, indirect, or both. Digital maturity is specified as a moderator of the AI adoption intensity–absorptive capacity relationship and as a boundary condition shaping the downstream indirect effect.

3. Methodology

3.1. Research Design

This study adopts a quantitative, explanatory, cross-sectional survey design to examine how and under what conditions AI adoption intensity enhances innovation performance in small and medium-sized enterprises (SMEs). The proposed model investigates both the internal capability-building mechanism and the boundary condition through which AI adoption becomes innovation-enhancing. Specifically, the model examines the sequential mediating roles of absorptive capacity and entrepreneurial agility, as well as the moderating role of digital maturity.

Partial least squares structural equation modeling (PLS-SEM) was selected as the main analytical approach. PLS-SEM is appropriate for this study because the model includes multiple reflective latent constructs, mediation paths, a moderation effect, and a prediction-oriented logic. The study is not limited to testing whether AI adoption is associated with innovation performance; rather, it seeks to explain and predict how AI adoption is translated into innovation-relevant capabilities in SMEs. The data were analyzed using SmartPLS, following established PLS-SEM assessment guidelines (Hair et al., 2022; Hair et al., 2019).

The unit of analysis is the firm. The key informants were individuals with sufficient knowledge of their firms' technology use, innovation activities, and managerial decision-making processes. These included owners, founders, CEOs, general managers, innovation managers, digital transformation/IT managers, operations managers, and marketing or sales managers.

3.2. Population, Sampling, and Data Collection

The empirical context of this study is Iran, a resource-constrained emerging economy in which SMEs increasingly face pressure to adopt digital and AI-enabled tools while operating under capability, institutional, and market-access constraints. This context is theoretically relevant because complementary digital capabilities, data readiness, absorptive capacity, and managerial digital skills cannot be assumed to be fully developed. It therefore provides a useful setting for examining the AI adoption–value gap in SMEs: whether adopting or experimenting with AI tools is sufficient to enhance innovation performance, or whether AI adoption becomes valuable only when firms possess the capabilities needed to absorb AI-enabled knowledge and convert it into entrepreneurial action.

This context is also relevant for global entrepreneurship research because SMEs operating under resource and institutional constraints often need to innovate adaptively and efficiently despite limited access to advanced technologies, financial resources, external knowledge sources, and international markets. Under such conditions, innovation is not only a growth-oriented activity but also a means of adaptation and survival. However, this does not imply that technology adoption alone is sufficient. Rather, such conditions make the role of complementary capabilities more visible. In this study, Iran therefore serves as an analytically useful context for testing whether absorptive capacity, entrepreneurial agility, and digital maturity explain how AI adoption becomes innovation-enhancing in resource-constrained SME environments.

The target population consisted of SMEs operating in Iran that had adopted, experimented with, or regularly used AI-based tools in at least one business activity. Since the study focuses on the realized use of AI rather than mere intention to adopt AI, respondents were screened based on whether their firms had used AI tools experimentally, regularly in one function, regularly in multiple functions, or in an advanced/integrated manner.

A purposive sampling strategy was used because the research required knowledgeable informants who were familiar with AI adoption and innovation-related activities in their firms. This approach is

appropriate when the research phenomenon requires respondents with direct managerial or operational knowledge rather than randomly selected individuals who may not be familiar with the firm's AI-related practices.

The survey was administered to SME decision-makers and managers across several industries, including ICT/software, manufacturing, services, retail/wholesale, tourism/hospitality, and creative/media sectors. Responses were screened for completeness, SME eligibility, relevance to AI use, and internal consistency. The final analytical sample consisted of 294 valid responses. No firms reporting complete non-use of AI were retained in the final dataset, ensuring alignment between the empirical sample and the conceptual scope of the study.

3.3. Sample Profile

Table 1 presents the characteristics of the final sample. The sample includes firms from diverse sectors, with the largest groups operating in ICT/software, manufacturing, and services. Regarding firm size, small firms represented the largest share of the sample, followed by medium-sized and micro firms. The respondents were primarily owners/founders, CEOs/general managers, innovation managers, and digital transformation/IT managers, suggesting that the data were provided by informants with relevant strategic, technological, or innovation-related knowledge.

Table 1
Sample characteristics

Category	Sub-category	Frequency	Percentage
Industry	ICT/Software	69	23.5%
	Manufacturing	58	19.7%
	Services	43	14.6%
	Retail/Wholesale	39	13.3%
	Tourism/Hospitality	32	10.9%
	Creative/Media	29	9.9%
	Other	24	8.2%
Firm size	Micro (1–9 employees)	75	25.5%
	Small (10–49 employees)	129	43.9%
	Medium (50–249 employees)	90	30.6%
Respondent role	Owner/Founder	84	28.6%
	CEO/General Manager	67	22.8%
	Innovation Manager	42	14.3%
	Digital Transformation/IT Manager	39	13.3%
	Operations Manager	33	11.2%
	Marketing/Sales Manager	29	9.9%
AI usage level	Experimental use	43	14.6%
	Regular use in one function	99	33.7%
	Regular use in multiple functions	92	31.3%
	Advanced/integrated use	60	20.4%
Continuous characteristics	Number of employees	Mean = 59.60	SD = 69.59
	Firm age	Mean = 11.00 years	SD = 5.45

The distribution of AI usage levels indicates that the sample includes SMEs at different stages of AI adoption. This variation is useful for testing the proposed model because the study examines differences in AI adoption intensity rather than treating AI adoption as a simple binary condition.

3.4. Measurement Instrument

The measurement instrument was developed by adapting items from previously validated scales and relevant prior studies. The questionnaire was not purely researcher-made. Rather, it was constructed by adapting established measures and contextually modifying them to fit the setting of AI adoption and innovation in SMEs.

This distinction is important. Some constructs, particularly absorptive capacity, have strong validated measurement foundations and were adapted more directly from prior scales. Other constructs, such as AI adoption intensity, entrepreneurial agility, and digital maturity, required more contextual adaptation because the study focuses specifically on AI-enabled innovation in SMEs. Therefore, the instrument is best described as adapted and contextually modified from validated scales and relevant literature.

All perceptual items were measured using a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. A seven-point scale was used to capture sufficient response variation while remaining understandable for managerial respondents.

3.5. Construct Operationalization and Source Basis

Table 2 summarizes the source basis and adaptation logic for each construct. The table explicitly distinguishes between constructs adapted from validated scales and constructs adapted and contextualized from broader literature streams.

Table 2
Construct operationalization and measurement source basis

Construct	Number of items	Main source basis	Claim type	Operationalization logic
AI Adoption Intensity	6	AI capability and AI adoption literature, particularly Mikalef and Gupta (2021), SME AI adoption studies, and OECD work on AI adoption in SMEs	Adapted and contextually modified	Measures the extent and functional scope of AI use in decision-making, customer and market analysis, product/service development, process improvement, opportunity identification, and strategic/operational decision support.
Absorptive Capacity	8	Flatten et al. (2011) and the absorptive capacity literature	Adapted from a validated scale	Covers knowledge acquisition, assimilation, transformation, and exploitation. This construct has the strongest direct validated measurement foundation.
Entrepreneurial Agility	6	Organizational agility, strategic agility, and entrepreneurial agility literature, including Sambamurthy et al. (2003), Lu and Ramamurthy (2011), and Karimi and Walter (2015)	Adapted and contextualized for SMEs	Captures opportunity recognition, rapid response, experimentation, resource reconfiguration, decision speed under uncertainty, and business model flexibility.
SME Innovation Performance	6	Oslo Manual, Wang and Ahmed (2004), Gunday et al. (2011), and innovation performance literature	Adapted and aligned	Reflects product/service innovation, business process innovation, customer/market-related innovation, business model innovation, commercialization of ideas, and comparative innovation outcomes.
Digital Maturity	7	SME digital maturity and digital transformation maturity literature, including digital maturity frameworks and SME digital readiness assessments	Adapted and contextualized	Captures digital infrastructure, integrated digital tools, data readiness, employee digital skills, digital culture, top management support, and continuous investment in digital capabilities.

This operationalization strategy reduces the risk of construct ambiguity. Absorptive capacity and innovation performance are grounded in well-established measurement traditions, while AI adoption intensity, entrepreneurial agility, and digital maturity are carefully adapted to the AI-SME context.

3.6. Measures

Five reflective constructs were measured in this study: AI adoption intensity, absorptive capacity, entrepreneurial agility, SME innovation performance, and digital maturity. The following subsections describe the conceptual meaning, source basis, and operationalization of each construct, while the complete list of measurement items is reported in Supplementary Table S1.

3.6.1. AI Adoption Intensity

AI adoption intensity refers to the extent to which SMEs use AI-based tools in actual business activities. Rather than measuring general awareness of AI or intention to adopt AI, this construct captures the functional use of AI in decision-making, customer and market analysis, product/service development, process improvement, opportunity identification, and strategic or operational decision support.

The items were adapted and contextually modified from the AI capability and AI adoption literature. In particular, the measurement logic builds on prior work on AI capability and its organizational consequences (Mikalef & Gupta, 2021), as well as the SME AI adoption literature and policy-oriented work emphasizing the importance of AI use in SMEs. Contextual modification was necessary because AI adoption in SMEs is often operationalized through accessible digital tools, analytics platforms, automation systems, recommendation systems, or generative AI applications rather than through large-scale proprietary AI infrastructures.

The items were:

AIAD1. Our firm uses AI-based tools to support business decision-making.

AIAD2. Our firm uses AI to analyze customer needs and market trends.

AIAD3. Our firm applies AI tools to support product or service development.

AIAD4. Our firm uses AI to improve or automate internal business processes.

AIAD5. Our firm uses AI to identify new business opportunities.

AIAD6. Our firm integrates AI-generated insights into strategic or operational decisions.

The construct was modeled reflectively because the indicators represent manifestations of the broader underlying intensity of AI adoption. SMEs with higher AI adoption intensity are expected to report greater use of AI across these related business activities.

3.6.2. Absorptive Capacity

Absorptive capacity refers to the firm's ability to identify, acquire, assimilate, transform, and exploit external knowledge. This construct is central to the proposed model because AI adoption can generate data, predictions, and insights, but these outputs become strategically valuable only when the firm can understand, integrate, and apply them.

Absorptive capacity was measured using items adapted from established absorptive capacity scales, particularly the scale development and validation work of Flatten et al. (2011). The eight items were designed to cover the four core components of absorptive capacity: knowledge acquisition, assimilation, transformation, and exploitation.

The items were:

ACAP1. Our firm regularly identifies valuable external knowledge relevant to its business.

ACAP2. Our firm frequently acquires new knowledge from customers, suppliers, competitors, or partners.

ACAP3. Our firm quickly understands new technological knowledge relevant to its business.

ACAP4. Our firm is effective at analyzing and interpreting newly acquired knowledge.

ACAP5. Our firm combines new knowledge with its existing knowledge base.

ACAP6. Our firm transforms new knowledge into practical business applications.

ACAP7. Our firm applies new knowledge to improve products, services, or processes.

ACAP8. Our firm effectively uses newly acquired knowledge for commercial or strategic purposes.

The construct was modeled reflectively because the items are expected to co-vary as indicators of the firm's broader knowledge absorption capability.

3.6.3. Entrepreneurial Agility

Entrepreneurial agility refers to the firm's ability to rapidly recognize opportunities, respond to market changes, experiment with new ideas, reconfigure resources, and make entrepreneurial decisions under uncertainty. In this study, entrepreneurial agility represents the action-oriented capability through which absorbed knowledge is translated into innovation-related behavior.

The items were adapted from the organizational agility, strategic agility, and entrepreneurial agility literatures. The operationalization draws on the idea that digital technologies can shape organizational agility and competitive action (Sambamurthy et al., 2003), on the distinction between market capitalizing agility and operational adjustment agility (Lu & Ramamurthy, 2011), and on the entrepreneurial agility perspective in digital entrepreneurship and value creation (Karimi & Walter, 2015). The adaptation was

necessary because entrepreneurial agility in SMEs is not merely operational flexibility; it involves opportunity sensing, rapid experimentation, flexible resource mobilization, and action under uncertainty.

The items were:

EAG1. Our firm quickly recognizes emerging market opportunities.

EAG2. Our firm rapidly responds to changes in customer needs.

EAG3. Our firm experiments with new business ideas faster than competitors.

EAG4. Our firm quickly reallocates resources to pursue promising opportunities.

EAG5. Our firm makes rapid entrepreneurial decisions under uncertainty.

EAG6. Our firm flexibly changes its products, services, or business model when new opportunities arise.

The construct was modeled reflectively because the items represent different but related manifestations of an underlying entrepreneurial agility capability.

3.6.4. SME Innovation Performance

SME innovation performance refers to the extent to which a firm introduces new or significantly improved products, services, processes, customer-related methods, and business models, and converts new ideas into marketable offerings. The construct was operationalized in line with prior innovation performance measures and aligned with the Oslo Manual's conceptualization of business innovation (OECD/Eurostat, 2018). The item structure also draws on established organizational innovativeness and innovation performance research (Wang & Ahmed, 2004; Gunday et al., 2011).

The items capture both product/service innovation and business process-related innovation. They also include customer/market-related innovation, business model innovation, commercialization of new ideas, and comparative innovation outcomes.

The items were:

INNP1. Our firm frequently introduces new or significantly improved products or services.

INNP2. Our firm frequently improves its internal business processes through new methods or technologies.

INNP3. Our firm develops new ways to reach, interact with, or serve customers.

INNP4. Our firm introduces new or significantly improved business models or revenue models.

INNP5. Our firm successfully converts new ideas into marketable products, services, or processes.

INNP6. Compared with our main competitors, our firm has achieved stronger innovation outcomes.

The construct was modeled reflectively because the items are treated as manifestations of the firm's overall innovation performance.

3.6.5. Digital Maturity

Digital maturity refers to the extent to which an SME possesses the digital infrastructure, integrated tools, data readiness, employee digital skills, digital culture, managerial support, and investment orientation required to use advanced digital technologies effectively. In the proposed model, digital maturity is treated as a boundary condition that strengthens the relationship between AI adoption intensity and absorptive capacity.

The items were adapted from SME digital maturity and digital transformation maturity literature. They were contextualized to capture the dimensions most relevant to AI use in SMEs: infrastructure, integration, data, skills, culture, leadership support, and continuous digital investment. This operationalization is consistent with digital maturity frameworks that emphasize technology, people, processes, culture, leadership, and data readiness as key dimensions of digital transformation capability.

The items were:

DMAT1. Our firm has adequate digital infrastructure to support advanced technologies.

DMAT2. Our firm uses integrated digital tools across key business functions.

DMAT3. Our firm has reliable and accessible data for decision-making.

DMAT4. Employees in our firm have sufficient digital skills to use advanced technologies.

DMAT5. Our firm has a culture that supports digital transformation.

DMAT6. Top management actively supports digital initiatives.

DMAT7. Our firm continuously invests in digital tools, data systems, and digital capabilities.

The construct was modeled reflectively because the indicators represent related manifestations of the firm's overall digital maturity.

3.7. Questionnaire Development and Content Validity

The questionnaire was developed in several stages. First, the relevant literature was reviewed to identify validated scales and theoretically relevant dimensions for each construct. Second, items were adapted and, where necessary, contextually modified to reflect the AI-SME setting. Third, the wording of the items was refined to ensure that managerial respondents could answer them based on their firms' actual practices rather than abstract perceptions.

Because several items were contextually modified, content validity was addressed through expert review. The initial questionnaire was reviewed by academic experts familiar with innovation, entrepreneurship, technology management, and PLS-SEM, as well as SME practitioners with experience in digital transformation or AI use. The reviewers assessed item clarity, construct relevance, wording precision, and contextual fit. Based on their feedback, minor wording adjustments were made to improve readability and reduce ambiguity.

A pilot test was then conducted before the main data collection. The pilot test helped assess whether respondents understood the item wording, whether the scale format was clear, and whether the questionnaire could be completed without excessive burden. The final version of the questionnaire was used for the main survey after these refinements.

3.8. Common Method Bias and Procedural Remedies

Because the data were collected through a single survey instrument, common method bias was considered during the research design. Several procedural remedies were used to reduce this risk. Respondents were informed that there were no right or wrong answers and were asked to respond based on their firm's actual practices. The questionnaire assured confidentiality and anonymity to reduce evaluation apprehension. The items were worded clearly and neutrally, and predictor and criterion constructs were separated within the questionnaire to reduce respondents' tendency to infer the hypothesized relationships. These remedies are consistent with established recommendations for reducing common method bias in survey-based research (Podsakoff et al., 2003).

In addition to procedural safeguards, the empirical analysis included collinearity diagnostics. Full collinearity and inner VIF values were inspected to assess whether collinearity posed a concern for the interpretation of the results (Kock, 2015). While no single procedure can fully eliminate concerns about common method bias, the combination of procedural remedies, reliable measurement properties, discriminant validity evidence, and acceptable collinearity diagnostics reduces the likelihood that the findings are solely attributable to method bias.

3.9. Data Analysis Procedure

The data were analyzed using SmartPLS. The analysis followed the two-step PLS-SEM assessment procedure recommended in the methodological literature: first, the measurement model was evaluated; second, the structural model was assessed (Hair et al., 2022; Hair et al., 2019).

For the reflective measurement model, indicator loadings, Cronbach's alpha, rho_A, composite reliability, average variance extracted, and discriminant validity were assessed. Indicator loadings above 0.70 were considered desirable. Internal consistency reliability was assessed using Cronbach's alpha, rho_A, and composite reliability, with values above 0.70 indicating acceptable reliability. Convergent validity was assessed using AVE, with values above 0.50 indicating that the construct explains more than half of the variance in its indicators. Discriminant validity was assessed using the heterotrait-monotrait ratio and

the Fornell-Larcker criterion. HTMT was emphasized because it is considered a more sensitive criterion for discriminant validity in variance-based SEM (Henseler et al., 2015; Fornell & Larcker, 1981).

The structural model was evaluated using collinearity statistics, path coefficients, coefficients of determination, effect sizes, mediation effects, moderation effects, and predictive relevance. Inner VIF values were examined to ensure that collinearity did not bias the path estimates. The significance of the direct, indirect, and interaction effects was assessed using bootstrapping with 5,000 subsamples, two-tailed testing, and bias-corrected confidence intervals. The sequential mediation effect was tested through the indirect path from AI adoption intensity to SME innovation performance via absorptive capacity and entrepreneurial agility.

The moderating effect of digital maturity was tested by creating an interaction term between AI adoption intensity and digital maturity. The interaction term was specified to predict absorptive capacity, thereby testing whether digital maturity strengthens the relationship between AI adoption intensity and absorptive capacity. A two-stage approach was used because it is appropriate for estimating latent variable interaction effects in PLS-SEM, particularly when the model includes reflective constructs and the interest is in the interaction between latent variables (Hair et al., 2022).

Finally, PLSpredict was conducted to evaluate the model's out-of-sample predictive relevance. The assessment focused primarily on SME innovation performance as the final target construct. Predictive relevance was evaluated using Q^2_predict values and prediction error comparisons between the PLS-SEM model and the linear model benchmark. RMSE was used as the main prediction error metric, while MAE was inspected as an additional robustness indicator. This approach follows the PLSpredict logic proposed for predictive model assessment in PLS-SEM (Shmueli et al., 2019).

4. Results

4.1. Overview of the PLS-SEM Assessment

The proposed model was examined using partial least squares structural equation modeling. The analysis proceeded in four stages. First, the measurement model was assessed by examining indicator loadings, internal consistency reliability, convergent validity, and discriminant validity. Second, the structural model was evaluated using collinearity diagnostics, path coefficients, coefficients of determination, and effect sizes. Third, bootstrapping with 5,000 subsamples was used to test the significance of direct, indirect, serial mediation, and moderation effects. Fourth, PLSpredict was conducted to assess the model's out-of-sample predictive relevance, with particular emphasis on SME innovation performance as the final target construct.

The model included five reflective latent constructs: AI adoption intensity, absorptive capacity, digital maturity, entrepreneurial agility, and SME innovation performance. The interaction term between AI adoption intensity and digital maturity was created to test whether digital maturity moderates the relationship between AI adoption intensity and absorptive capacity. Since the interaction term is a

derived construct used for moderation testing, it is not interpreted as a substantive reflective construct in the measurement model assessment.

4.2. Measurement Model Assessment

4.2.1. Indicator Reliability, Internal Consistency Reliability, and Convergent Validity

The measurement model results indicate satisfactory psychometric properties. All reflective indicator loadings exceeded the commonly recommended threshold of 0.70. The lowest loading was observed for EAG5, with a loading of 0.718, which remains above the acceptable minimum. The remaining loadings ranged from 0.750 to 0.873 across the constructs, indicating adequate indicator reliability. The complete list of outer loadings is provided in Supplementary Table S2.

Internal consistency reliability was assessed using Cronbach's alpha, rho_A, and composite reliability. As shown in Table 3, Cronbach's alpha values ranged from 0.888 to 0.931, rho_A values ranged from 0.893 to 0.937, and composite reliability values ranged from 0.915 to 0.944. These values indicate satisfactory internal consistency without suggesting excessive redundancy among the indicators. Convergent validity was assessed through the average variance extracted. The AVE values ranged from 0.633 to 0.706, exceeding the recommended threshold of 0.50. Therefore, convergent validity was established for all reflective constructs.

Table 3
Measurement model assessment

Construct	Items	Loading range	Cronbach's alpha	rho_A	Composite reliability	AVE
Absorptive Capacity	8	0.750–0.829	0.917	0.918	0.932	0.633
AI Adoption Intensity	6	0.777–0.847	0.906	0.910	0.927	0.681
Digital Maturity	7	0.807–0.873	0.931	0.937	0.944	0.706
Entrepreneurial Agility	6	0.718–0.850	0.888	0.893	0.915	0.642
SME Innovation Performance	6	0.760–0.827	0.893	0.894	0.918	0.651

Overall, the measurement model demonstrates satisfactory indicator reliability, internal consistency reliability, and convergent validity.

4.2.2. Discriminant Validity

Discriminant validity was evaluated using the heterotrait-monotrait ratio. As shown in Table 4, all HTMT values were below the conservative threshold of 0.85. The highest HTMT value was observed between entrepreneurial agility and SME innovation performance (0.700), which remains comfortably below the threshold. These results indicate that the constructs are empirically distinct from one another.

Table 4
HTMT results

Construct pair	HTMT
AIAD – ACAP	0.514
DMAT – ACAP	0.377
DMAT – AIAD	0.330
EAG – ACAP	0.670
EAG – AIAD	0.413
EAG – DMAT	0.399
INNP – ACAP	0.569
INNP – AIAD	0.379
INNP – DMAT	0.453
INNP – EAG	0.700

The Fornell-Larcker criterion also supported discriminant validity. The square roots of AVE values were higher than the inter-construct correlations for their respective constructs. The full Fornell-Larcker matrix is reported in Supplementary Table S3. Taken together, the HTMT and Fornell-Larcker results provide sufficient evidence of discriminant validity.

4.3. Structural Model Assessment

Before evaluating the structural relationships, collinearity among predictor constructs was assessed using inner VIF values. The VIF values ranged from 1.009 to 1.780, which are well below commonly used cut-off values. Therefore, collinearity was not considered a threat to the interpretation of the structural model.

The explanatory power of the model was assessed using R^2 values (Table 5). The model explained 28.6% of the variance in absorptive capacity, 37.8% of the variance in entrepreneurial agility, and 42.5% of the variance in SME innovation performance. These values indicate that the model provides a meaningful level of explanatory power, particularly for the final outcome construct, SME innovation performance.

Table 5
Coefficients of determination

Endogenous construct	R^2	Adjusted R^2
Absorptive Capacity	0.286	0.279
Entrepreneurial Agility	0.378	0.373
SME Innovation Performance	0.425	0.420

Effect sizes were also examined using f^2. The strongest effect was observed for absorptive capacity on entrepreneurial agility ($f^2 = 0.385$), followed by entrepreneurial agility on SME innovation performance ($f^2 = 0.254$) and AI adoption intensity on absorptive capacity ($f^2 = 0.194$). The moderating effect of AI adoption intensity × digital maturity on absorptive capacity had a small but meaningful effect size ($f^2 = 0.022$), which is common in moderation analysis.

Table 6
Collinearity and effect size assessment

Path	VIF	f^2
AIAD → ACAP	1.108	0.194
DMAT → ACAP	1.111	0.075
AIAD × DMAT → ACAP	1.009	0.022
ACAP → EAG	1.285	0.385
AIAD → EAG	1.285	0.015
EAG → INNP	1.606	0.254
ACAP → INNP	1.780	0.033
AIAD → INNP	1.304	0.008

Common method bias was also considered through the procedural remedies described in the methodology section and through collinearity-based diagnostics. The available diagnostics did not indicate severe inflation. As reported in Table 6, inner VIF values were low, ranging from 1.009 to 1.780. In addition, outer VIF values are reported in Supplementary Table S4 and did not indicate problematic indicator-level multicollinearity; the highest outer VIF was observed for DMAT6 (3.331), which remains below the conventional threshold of 5. Together, these diagnostics suggest that collinearity and common method bias are unlikely to be serious threats to the interpretation of the results. Nevertheless, this evidence is interpreted as supportive rather than definitive, and the findings are evaluated primarily through the measurement model, discriminant validity, structural paths, and predictive assessment.

Model fit indices were also inspected as supplementary evidence. The saturated model SRMR was 0.043 and the estimated model SRMR was 0.063, both below the commonly used 0.08 threshold. The NFI

values were 0.895 for the saturated model and 0.892 for the estimated model, while rms Theta was 0.095. Although global fit indices are not the primary basis for assessing PLS-SEM models, these values do not suggest any serious model fit concern.

Note

The figure displays standardized path coefficients, outer loadings, and R^2 values obtained from the PLS Algorithm.

4.4. Direct Effects and Hypothesis Testing

Bootstrapping with 5,000 subsamples was used to assess the significance of the structural paths. The results are reported in Table 7.

AI adoption intensity had a positive and significant effect on absorptive capacity ($\beta = 0.391$, $t = 8.013$, $p < 0.001$), supporting H1. This indicates that SMEs using AI more intensively are better positioned to identify, assimilate, and apply relevant knowledge. Absorptive capacity had a strong positive effect on entrepreneurial agility ($\beta = 0.555$, $t = 12.144$, $p < 0.001$), supporting H2. Entrepreneurial agility, in turn, had a positive and significant effect on SME innovation performance ($\beta = 0.484$, $t = 9.450$, $p < 0.001$), supporting H3.

The direct effect of AI adoption intensity on entrepreneurial agility was positive and significant, although relatively weak in magnitude ($\beta = 0.110$, $t = 2.141$, $p = 0.031$), supporting H4. Absorptive capacity also had a positive and significant direct effect on SME innovation performance ($\beta = 0.185$, $t = 3.044$, $p = 0.003$), supporting H5. By contrast, the direct effect of AI adoption intensity on SME innovation performance was positive but not statistically significant ($\beta = 0.079$, $t = 1.446$, $p = 0.142$); therefore, H6 was not supported.

The non-significant direct effect of AI adoption intensity on SME innovation performance is theoretically informative. It suggests that AI adoption does not automatically translate into innovation performance. Instead, its effect appears to operate mainly through organizational and entrepreneurial capability mechanisms, particularly absorptive capacity and entrepreneurial agility.

Digital maturity had a positive and significant main effect on absorptive capacity ($\beta = 0.243$, $t = 5.028$, $p < 0.001$). This path was included as part of the moderation model and is reported for completeness. The interaction term between AI adoption intensity and digital maturity was also positive and significant in predicting absorptive capacity ($\beta = 0.128$, $t = 2.577$, $p = 0.008$). The bias-corrected confidence interval did not include zero [0.031, 0.222]. This result supports H10 and indicates that the relationship between AI adoption intensity and absorptive capacity is stronger when digital maturity is higher.

Table 7
Direct effects and hypothesis testing

Hypothesis	Path	β	STDEV	t-value	p-value	95% BCa CI	Result
H1	AIAD → ACAP	0.391	0.048	8.013	< 0.001	[0.295, 0.481]	Supported
—	DMAT → ACAP	0.243	0.048	5.028	< 0.001	[0.146, 0.335]	Main effect included in moderation model
H10	AIAD × DMAT → ACAP	0.128	0.048	2.577	0.008	[0.031, 0.222]	Supported
H2	ACAP → EAG	0.555	0.046	12.144	< 0.001	[0.456, 0.636]	Supported
H4	AIAD → EAG	0.110	0.051	2.141	0.031	[0.008, 0.208]	Supported, weak effect
H3	EAG → INNP	0.484	0.052	9.450	< 0.001	[0.379, 0.585]	Supported
H5	ACAP → INNP	0.185	0.061	3.044	0.003	[0.065, 0.303]	Supported
H6	AIAD → INNP	0.079	0.054	1.446	0.142	[-0.025, 0.187]	Not supported

Note

The figure displays bootstrapped t-values for the structural paths based on 5,000 bootstrap subsamples.

4.5. Mediation, Serial Mediation, and Moderated Indirect Effects

The indirect effects were examined to clarify the mechanisms through which AI adoption intensity influences SME innovation performance. The results are presented in Table 8.

First, AI adoption intensity had a significant indirect effect on entrepreneurial agility through absorptive capacity (β = 0.217, t = 6.844, p < 0.001, 95% BCa CI [0.158, 0.280]). This result supports H7 and indicates that AI adoption contributes to entrepreneurial agility partly by strengthening the firm's absorptive capacity.

Second, absorptive capacity had a significant indirect effect on SME innovation performance through entrepreneurial agility (β = 0.269, t = 7.317, p < 0.001, 95% BCa CI [0.200, 0.344]). This supports H8 and suggests that absorptive capacity enhances innovation performance not only directly but also by enabling more agile entrepreneurial responses.

Third, and most importantly, the serial indirect effect from AI adoption intensity to SME innovation performance through absorptive capacity and entrepreneurial agility was positive and significant (β = 0.105, t = 5.345, p < 0.001, 95% BCa CI [0.071, 0.147]). This supports H9 and confirms the proposed capability-building mechanism. Specifically, AI adoption intensity first strengthens absorptive capacity, which then enhances entrepreneurial agility, which ultimately improves SME innovation performance.

The total effect of AI adoption intensity on SME innovation performance was positive and significant (β = 0.310, t = 6.218, p < 0.001), whereas the direct effect was not significant. This pattern indicates that the effect of AI adoption intensity on SME innovation performance is primarily indirect. In substantive terms, AI adoption becomes innovation-enhancing when SMEs are able to translate AI-enabled insights into absorptive capacity and entrepreneurial agility.

The results also provide evidence consistent with a moderated indirect mechanism. The indirect path from the interaction term to entrepreneurial agility through absorptive capacity was significant (β = 0.071, t = 2.583, p = 0.010, 95% BCa CI [0.019, 0.126]). More importantly, the serial moderated indirect path from the interaction term to SME innovation performance through absorptive capacity and entrepreneurial agility was positive and significant (β = 0.034, t = 2.534, p = 0.011, 95% BCa CI [0.010, 0.063]). This result supports H11 and suggests that digital maturity strengthens the capability-building pathway through which AI adoption intensity contributes to innovation performance. However, the shorter moderated indirect path from AI adoption intensity × digital maturity to innovation performance through absorptive capacity alone was only marginal based on the p-value (β = 0.024, t = 1.850, p = 0.064), although its confidence interval did not include zero. Therefore, this shorter path is interpreted cautiously and treated as supplementary evidence rather than the core moderated mediation result.

Table 8
Indirect, serial mediation, and moderated indirect effects

Hypothesis	Indirect path	β	STDEV	t-value	p-value	95% BCa CI	Interpretation
H7	AIAD → ACAP → EAG	0.217	0.032	6.844	< 0.001	[0.158, 0.280]	Supported
—	AIAD → ACAP → INNP	0.072	0.026	2.775	0.006	[0.026, 0.127]	Supplementary indirect effect supported
—	AIAD → EAG → INNP	0.053	0.026	2.018	0.044	[0.004, 0.108]	Supplementary indirect effect supported, weak
H8	ACAP → EAG → INNP	0.269	0.037	7.317	< 0.001	[0.200, 0.344]	Supported
H9	AIAD → ACAP → EAG → INNP	0.105	0.020	5.345	< 0.001	[0.071, 0.147]	Supported
—	AIAD × DMAT → ACAP → EAG	0.071	0.027	2.583	0.010	[0.019, 0.126]	Supplementary moderated indirect effect supported
—	AIAD × DMAT → ACAP → INNP	0.024	0.013	1.850	0.064	[0.005, 0.056]	Weak/mixed supplementary evidence
H11	AIAD × DMAT → ACAP → EAG → INNP	0.034	0.014	2.534	0.011	[0.010, 0.063]	Supported

The evidence is strongest for the serial mediation mechanism and for the moderation of the initial AI adoption intensity–absorptive capacity link. These findings support the central argument of the study: AI adoption enhances SME innovation performance mainly when it is translated into absorptive capacity and entrepreneurial agility, and this translation is stronger under higher levels of digital maturity.

4.6. Moderation Plot

To further interpret the significant interaction effect, a moderation plot was generated for the relationship between AI adoption intensity and absorptive capacity at three levels of digital maturity: one standard deviation below the mean, the mean, and one standard deviation above the mean. As shown in Fig. 4, the slope of the AI adoption intensity–absorptive capacity relationship is steeper when digital

maturity is high. This indicates that SMEs with higher digital maturity are better able to convert AI adoption intensity into absorptive capacity.

The plot also shows that the relationship between AI adoption intensity and absorptive capacity remains positive across different levels of digital maturity, but its strength differs substantially. At higher levels of digital maturity, increases in AI adoption intensity are associated with a stronger increase in absorptive capacity. At lower levels of digital maturity, the relationship is weaker. This pattern is consistent with the positive and significant interaction effect reported in Table 7 and provides visual support for H10.

Note

The figure shows the predicted relationship between AI adoption intensity and absorptive capacity at low, mean, and high levels of digital maturity.

4.7. PLSpredict Assessment

PLSpredict was conducted to assess the model's out-of-sample predictive relevance. The analysis focused on the manifest indicators of the endogenous constructs, with particular emphasis on SME innovation performance as the final outcome construct. Predictive relevance was evaluated using Q^2_predict values and prediction error comparisons between the PLS-SEM model and the linear model benchmark.

For SME innovation performance, all six indicators had positive Q^2_predict values, ranging from 0.071 to 0.141 (Table 9). This indicates that the model has predictive relevance at the indicator level for the final target construct. In addition, the PLS-SEM model produced lower RMSE values than the linear model benchmark for all six innovation performance indicators. The MAE comparison was more mixed: the PLS-SEM model outperformed the linear benchmark for three of the six indicators, while the remaining differences were small and favored the linear benchmark. Therefore, the PLSpredict results should be interpreted as indicating satisfactory indicator-level predictive performance rather than uniformly strong predictive power across all error metrics.

Table 9
PLSpredict results for SME innovation performance

Indicator	Q^2_predict	PLS RMSE	LM RMSE	RMSE result	PLS MAE	LM MAE	MAE result
INNP1	0.120	1.730	1.745	PLS better	1.442	1.439	LM slightly better
INNP2	0.111	1.654	1.658	PLS better	1.363	1.345	LM better
INNP3	0.141	1.618	1.652	PLS better	1.356	1.374	PLS better
INNP4	0.071	1.737	1.761	PLS better	1.457	1.463	PLS better
INNP5	0.137	1.650	1.657	PLS better	1.366	1.364	LM slightly better
INNP6	0.137	1.678	1.719	PLS better	1.407	1.436	PLS better

Across all endogenous construct indicators, all Q^2_predict values were positive and the PLS-SEM model produced lower RMSE values than the linear model benchmark. The MAE results were also largely favorable, although not uniformly so. These findings provide additional support for the model's indicator-level predictive relevance, particularly for SME innovation performance. The full PLSpredict results for all endogenous indicators are provided in Supplementary Table S5.

4.8. Summary of Hypothesis Testing

Table 10 summarizes the results of all hypotheses. The findings support the proposed capability-based model. H1, H2, and H3 were supported, confirming the core path from AI adoption intensity to absorptive capacity, from absorptive capacity to entrepreneurial agility, and from entrepreneurial agility to SME innovation performance. H4 and H5 were also supported, although the direct effect of AI adoption intensity on entrepreneurial agility was relatively weak. H6 was not supported, as AI adoption intensity did not have a significant direct effect on SME innovation performance.

The mediation hypotheses were supported. H7 and H8 confirmed the mediating roles of absorptive capacity and entrepreneurial agility, respectively. H9 was also supported, confirming the serial mediation mechanism from AI adoption intensity to SME innovation performance through absorptive capacity and entrepreneurial agility. H10 was supported, showing that digital maturity positively moderates the relationship between AI adoption intensity and absorptive capacity. Finally, H11 was supported, indicating that digital maturity strengthens the indirect serial pathway through which AI adoption intensity enhances SME innovation performance.

Table 10
Summary of hypothesis testing

Hypothesis	Statement	Result
H1	AI adoption intensity positively affects absorptive capacity.	Supported
H2	Absorptive capacity positively affects entrepreneurial agility.	Supported
H3	Entrepreneurial agility positively affects SME innovation performance.	Supported
H4	AI adoption intensity positively affects entrepreneurial agility.	Supported, weak effect
H5	Absorptive capacity positively affects SME innovation performance.	Supported
H6	AI adoption intensity positively affects SME innovation performance.	Not supported
H7	Absorptive capacity mediates the relationship between AI adoption intensity and entrepreneurial agility.	Supported
H8	Entrepreneurial agility mediates the relationship between absorptive capacity and SME innovation performance.	Supported
H9	Absorptive capacity and entrepreneurial agility sequentially mediate the relationship between AI adoption intensity and SME innovation performance.	Supported
H10	Digital maturity positively moderates the relationship between AI adoption intensity and absorptive capacity.	Supported
H11	Digital maturity strengthens the indirect effect of AI adoption intensity on SME innovation performance through absorptive capacity and entrepreneurial agility.	Supported

The results provide consistent support for the proposed capability-based explanation of AI-enabled SME innovation. AI adoption intensity significantly enhances absorptive capacity, and absorptive capacity strongly predicts entrepreneurial agility. Entrepreneurial agility, in turn, significantly improves SME innovation performance. The direct effect of AI adoption intensity on SME innovation performance is not significant, whereas the total effect and the serial indirect effect are significant. This suggests that AI adoption is not sufficient by itself to generate innovation outcomes; instead, its innovation value depends on whether SMEs can transform AI-enabled insights into knowledge absorption and agile entrepreneurial action.

Digital maturity also plays an important boundary-condition role. The significant interaction between AI adoption intensity and digital maturity shows that digitally mature SMEs are more capable of converting AI adoption into absorptive capacity. The moderation plot further supports this interpretation by showing a steeper AI adoption intensity–absorptive capacity relationship under high digital maturity. Furthermore, the significant serial moderated indirect effect indicates that digital maturity strengthens the capability-

building process through which AI adoption contributes to entrepreneurial agility and innovation performance.

Overall, the empirical findings support the study's central argument: AI adoption enhances SME innovation performance primarily through a sequential process of absorptive capacity development and entrepreneurial agility, and this process is strengthened when SMEs possess higher levels of digital maturity.

5. Discussion

5.1. Discussion of Key Findings

The results provide a clear answer to the central question of this study: AI adoption enhances SME innovation performance not directly, but through a capability-building mechanism. The direct effect of AI adoption intensity on SME innovation performance was not statistically significant, whereas the total effect and the serial indirect effect were significant. This pattern indicates an indirect-only mediation mechanism, suggesting that AI adoption becomes innovation-enhancing when it is translated into absorptive capacity and entrepreneurial agility. In other words, AI adoption provides innovation-relevant potential, but this potential is realized only when SMEs are able to absorb AI-enabled knowledge and convert it into agile entrepreneurial action.

The non-significant direct effect of AI adoption intensity on SME innovation performance is one of the most theoretically important findings of this study. It should not be interpreted as evidence that AI adoption is unimportant. Rather, it shows that AI adoption alone is not sufficient to generate innovation outcomes in SMEs. Acquiring or using AI-based tools does not automatically make a firm more innovative. AI can provide data, predictions, automation, decision support, and market insights, but these technological inputs must be absorbed, interpreted, combined with existing knowledge, and converted into entrepreneurial action before they influence innovation performance. This finding challenges a simple technology-adoption logic and reinforces the capability-based argument of the study: AI adoption acts as an enabling input, whereas absorptive capacity and entrepreneurial agility function as the organizational mechanisms through which AI becomes innovation-relevant. This interpretation is consistent with research on general-purpose technologies and digital transformation, which emphasizes that technological adoption creates value only when combined with complementary intangible assets, organizational learning, managerial capabilities, and process adaptation (Brynjolfsson et al., 2021; Vial, 2019; Verhoef et al., 2021). Thus, the value of AI in SMEs lies less in adoption itself and more in the firm's ability to transform AI-enabled insights into knowledge absorption and agile innovation-oriented action.

The positive effect of AI adoption intensity on absorptive capacity supports this interpretation. SMEs that use AI more intensively appear better positioned to identify, acquire, assimilate, transform, and exploit relevant knowledge. This finding aligns with absorptive capacity theory, which argues that firms differ in their ability to recognize the value of external knowledge and apply it commercially (Cohen &

Levinthal, 1990; Zahra & George, 2002). It also complements AI capability research, which suggests that AI contributes to organizational outcomes through the development and orchestration of complementary capabilities rather than through technical deployment alone (Mikalef & Gupta, 2021; Enholm et al., 2022). In this study, AI adoption intensity functions as a knowledge-enabling input that strengthens the firm's ability to process and use external and internal knowledge.

The strong positive relationship between absorptive capacity and entrepreneurial agility further clarifies the mechanism. Absorptive capacity does not only help SMEs learn; it also enables them to act. Firms that are better at acquiring and transforming knowledge are more capable of recognizing emerging opportunities, responding to customer changes, experimenting with new ideas, reallocating resources, and making rapid decisions under uncertainty. This extends the absorptive capacity literature by showing that absorptive capacity can serve as an antecedent of entrepreneurial agility. It also supports the dynamic capabilities perspective, which emphasizes sensing, seizing, and reconfiguring capabilities in changing environments (Teece et al., 1997; Teece, 2007).

The positive effect of entrepreneurial agility on SME innovation performance confirms that innovation requires more than knowledge availability. SMEs must be able to convert knowledge into timely entrepreneurial action. Entrepreneurial agility appears to be the action-oriented capability through which absorbed knowledge becomes new or improved products, services, processes, customer-related methods, and business models. This finding is consistent with the organizational agility literature, which links agility to market responsiveness and operational adjustment (Sambamurthy et al., 2003; Lu & Ramamurthy, 2011), and with digital entrepreneurship research, which highlights experimentation, opportunity creation, and flexible value generation in digitally enabled environments (Nambisan, 2017; Nambisan et al., 2019).

The findings further show that digital maturity plays a critical boundary-condition role. The positive and significant interaction effect indicates that the relationship between AI adoption intensity and absorptive capacity is stronger when SMEs have higher levels of digital maturity. Digitally mature SMEs are more likely to have reliable data, integrated digital tools, digital skills, managerial support, and a culture supportive of digital transformation. These conditions make AI-generated insights more accessible, interpretable, shareable, and actionable. In contrast, SMEs with lower digital maturity may adopt AI tools but struggle to integrate them into knowledge routines and innovation processes.

Moreover, the significant moderated serial indirect effect suggests that digital maturity strengthens the downstream pathway through which AI adoption intensity enhances SME innovation performance via absorptive capacity and entrepreneurial agility. This provides a more precise explanation of when AI adoption becomes valuable. Digitally mature SMEs are better positioned to convert AI adoption into innovation-relevant capabilities because they possess the digital foundations required for AI-enabled learning and agile entrepreneurial response. This finding is consistent with digital transformation research, which argues that digital value creation depends on organizational readiness, data, processes,

culture, leadership, and dynamic capabilities rather than technology adoption alone (Vial, 2019; Warner & Wäger, 2019; Verhoef et al., 2021).

Beyond explanatory power, the PLSpredict results provide additional support for the proposed model. The model demonstrated satisfactory indicator-level predictive relevance for SME innovation performance, as all innovation performance indicators had positive Q^2_predict values and the PLS-SEM model produced lower RMSE values than the linear model benchmark for all six innovation performance indicators. Although the MAE results were more mixed, the overall PLSpredict evidence suggests that the proposed capability-based model has meaningful predictive relevance for SME innovation performance. This reinforces the argument that AI adoption contributes to innovation outcomes not merely as a technological input, but through the development of absorptive capacity and entrepreneurial agility under conditions of digital maturity.

Overall, the results support the central argument of the study: AI adoption does not automatically improve SME innovation performance. Instead, AI adoption becomes innovation-enhancing when SMEs possess the knowledge-processing capability to absorb AI-enabled insights and the entrepreneurial agility to act on them. Digital maturity strengthens this process by enabling SMEs to convert AI use into absorptive capacity and, ultimately, innovation performance.

5.2. Theoretical Contributions

This study makes four main theoretical contributions: First, the study contributes to AI adoption and innovation research by moving beyond a direct-effect perspective. Prior research has shown that AI can support creativity, decision-making, innovation management, and business value creation (Haefner et al., 2021; Mikalef & Gupta, 2021; Enholm et al., 2022). However, the mechanisms through which AI adoption produces innovation outcomes in SMEs remain insufficiently explained. This study shows that AI adoption intensity does not directly enhance SME innovation performance. Instead, its effect is transmitted through absorptive capacity and entrepreneurial agility. The contribution is therefore not simply the claim that AI matters for innovation, but the explanation of how AI becomes innovation-relevant through a sequential capability-building mechanism.

Second, the study contributes to absorptive capacity theory by positioning absorptive capacity as the knowledge-processing bridge between AI adoption and entrepreneurial action. Traditional absorptive capacity research emphasizes the importance of acquiring, assimilating, transforming, and exploiting knowledge for innovation (Cohen & Levinthal, 1990; Zahra & George, 2002; Flatten et al., 2011). This study extends that logic to AI-enabled SMEs by showing that AI adoption intensity strengthens absorptive capacity, and that absorptive capacity subsequently enhances entrepreneurial agility. Thus, absorptive capacity is not only a learning capability but also a foundation for rapid opportunity-oriented action.

Third, the study contributes to entrepreneurship and SME innovation research by identifying entrepreneurial agility as the action mechanism through which absorbed knowledge becomes innovation

performance. SMEs often innovate through rapid experimentation, customer-driven adaptation, flexible resource allocation, and business model adjustment rather than through highly formalized R&D systems. By showing that entrepreneurial agility mediates the relationship between absorptive capacity and innovation performance, this study links AI adoption research to entrepreneurship theory and explains how SMEs convert knowledge into innovation-related action.

This contribution is particularly relevant in emerging economy SME contexts, where resource limitations, institutional uncertainty, weaker digital infrastructure, and uneven access to advanced capabilities can make the AI adoption–value gap more visible. In such contexts, it is less appropriate to assume that firms already possess the data readiness, absorptive capacity, managerial digital skills, and digital maturity required to benefit from AI adoption. The findings therefore extend the global entrepreneurship relevance of the study by showing that AI-enabled innovation in SMEs depends not merely on technological access, but on the capability conditions under which entrepreneurial firms operate. This contextual setting strengthens the theoretical argument that AI adoption becomes innovation-enhancing only when SMEs can absorb AI-enabled knowledge and convert it into agile entrepreneurial action.

Fourth, the study contributes to digital transformation research by identifying digital maturity as a boundary condition in the AI adoption–innovation relationship. Prior digital transformation research emphasizes that digital value creation depends on organizational readiness, strategic renewal, culture, leadership, data, and dynamic capabilities (Vial, 2019; Warner & Wäger, 2019; Verhoef et al., 2021). This study adds that digital maturity strengthens the specific relationship between AI adoption intensity and absorptive capacity and reinforces the downstream indirect pathway to innovation performance. Digital maturity is therefore not treated as a background characteristic; it is theorized and empirically supported as a condition that shapes whether AI adoption becomes capability-enhancing.

Taken together, these contributions refine the understanding of AI-enabled SME innovation. The findings suggest that AI adoption should not be viewed as a standalone technological input. Rather, AI adoption should be understood as part of a capability-building process in which digital maturity enables knowledge absorption, knowledge absorption enables entrepreneurial agility, and entrepreneurial agility enables innovation performance.

5.3. Practical Implications

The findings offer several implications for SME owners, managers, entrepreneurs, and policymakers. First, SME managers should avoid treating AI adoption as a standalone solution. The non-significant direct effect of AI adoption intensity on innovation performance suggests that adopting AI tools is not enough. SMEs need to build internal routines for interpreting AI-generated insights, integrating them with existing knowledge, and applying them to products, services, processes, and business models. Managers should therefore invest not only in AI tools but also in knowledge management, employee learning, cross-functional communication, and mechanisms for using AI insights in decision-making.

Second, SMEs should strengthen absorptive capacity as a core AI-related capability. AI tools can generate data, predictions, recommendations, and market signals, but firms must be able to identify valuable knowledge, understand it, combine it with prior experience, and use it commercially. Practical steps include training employees to interpret AI outputs, creating routines for sharing AI-generated insights, connecting AI analytics to customer feedback, and encouraging collaboration between technical and business functions. In SMEs, where formal R&D structures may be limited, absorptive capacity can serve as a practical substitute for more formalized innovation systems.

Third, SMEs should convert absorbed knowledge into entrepreneurial agility. Knowledge absorption alone is not sufficient unless firms act on it. Managers should develop processes that allow rapid experimentation, fast customer feedback loops, flexible resource allocation, and business model adjustment. AI-generated insights should be connected to entrepreneurial decision-making rather than remaining confined to dashboards, isolated analytics tools, or technical functions. This is especially important for SMEs because their competitive advantage often depends on speed, flexibility, and closeness to market opportunities.

Fourth, digital maturity should be treated as a prerequisite for effective AI adoption. The significant moderating effect of digital maturity indicates that SMEs with stronger digital infrastructure, integrated tools, reliable data, employee digital skills, digital culture, and managerial support are better positioned to turn AI adoption into absorptive capacity. Managers should therefore assess their firm's digital maturity before scaling AI initiatives. In some cases, improving data quality, employee skills, system integration, or managerial commitment may be more urgent than adopting additional AI tools.

Fifth, policymakers and SME support institutions should design AI support programs that go beyond technology access. Subsidies, vouchers, and AI awareness programs may help SMEs experiment with AI, but they are unlikely to be sufficient if SMEs lack digital maturity and absorptive capacity. Support programs should combine AI adoption with training, data readiness support, digital maturity assessment, innovation capability development, and mentoring on business model experimentation. Incubators, accelerators, chambers of commerce, and SME development agencies can play an important role by helping SMEs connect AI tools to entrepreneurial opportunity recognition and innovation processes.

5.4. Limitations and Future Research

Despite its contributions, this study has several limitations that provide opportunities for future research. First, the study is based on cross-sectional survey data from SMEs operating in a single emerging economy context. Although this setting is theoretically relevant for examining AI adoption under capability and resource constraints, causal claims should be made cautiously and the generalizability of the findings to advanced economies or other institutional environments should be examined in future multi-country studies. Future research could use longitudinal and cross-country designs to examine how AI adoption, absorptive capacity, entrepreneurial agility, and innovation performance evolve over time across different economic and institutional settings. Such studies could also investigate whether the

benefits of AI adoption follow a delayed or J-curve pattern, as suggested in research on general-purpose technologies and intangible complements.

Second, the study relies on self-reported perceptual measures, including the measurement of AI adoption intensity and innovation performance. Although this approach is common in SME research and allows knowledgeable managers to report on the functional use of AI across business activities, it does not capture objective AI usage behavior. Managers' perceptions of AI adoption intensity may differ from actual usage frequency, system-level logs, investment levels, or the technical sophistication of deployed AI applications. Similarly, perceptual innovation performance may not fully reflect objective innovation outcomes. Future studies could therefore complement survey-based measures with objective indicators such as AI usage logs, the number of AI-enabled tools deployed, frequency of AI use across business functions, AI-related investment, digital trace data, new product counts, patent applications, sales from new products, or process improvement metrics. Multi-respondent designs could also improve reliability by collecting responses from both managerial and technical informants within the same firm. Such evidence would provide a more fine-grained understanding of how the actual use of AI technologies translates into capability development and innovation outcomes.

Third, the study focuses on SMEs that had adopted or experimented with AI tools. This design is appropriate for examining AI adoption intensity, but it does not explain why some SMEs do not adopt AI at all. Future research could compare non-adopters, experimental adopters, functional adopters, and advanced AI users to develop a more complete stage-based model of SME AI adoption and value creation.

Fourth, the study treats SMEs as a broad category. Although the sample includes firms from multiple sectors, AI adoption and innovation mechanisms may differ across manufacturing, services, ICT/software, retail, tourism, and creative industries. Future research could examine sector-specific models or conduct multi-group analysis to determine whether the capability-building pathway differs across industries, firm sizes, or levels of technological intensity.

Fifth, the study examines digital maturity as the key boundary condition. Future research could investigate additional moderators, such as environmental turbulence, competitive intensity, entrepreneurial orientation, leadership support, data quality, AI governance, employee resistance, trust in AI, and ethical AI readiness. These factors may further explain why some SMEs benefit more from AI adoption than others.

Sixth, the study examines absorptive capacity and entrepreneurial agility as the main mediating capabilities. Future studies could extend the model by incorporating other mechanisms, such as organizational learning, human–AI collaboration capability, data analytics capability, dynamic managerial capability, business model innovation capability, or responsible AI capability. Such extensions would provide a richer understanding of how AI adoption becomes strategically valuable in SMEs.

Finally, this study measures AI adoption intensity at the firm level without distinguishing between different types of AI applications. Future research could examine whether the proposed mechanism differs across predictive analytics, automation systems, recommendation systems, generative AI tools, customer-facing AI, or process-oriented AI applications. Such work would help clarify whether different forms of AI adoption require different capability configurations to generate innovation outcomes.

6. Conclusion

This study set out to answer a central question: when does AI adoption enhance SME innovation performance? The findings show that AI adoption intensity does not directly improve SME innovation performance. Instead, its effect is transmitted through a sequential capability-building mechanism in which AI adoption strengthens absorptive capacity, absorptive capacity enhances entrepreneurial agility, and entrepreneurial agility improves innovation performance. Digital maturity strengthens the initial AI adoption–absorptive capacity link and reinforces the downstream indirect pathway to innovation performance. The PLSpredict results further suggest that the model has satisfactory indicator-level predictive relevance for SME innovation performance.

Overall, the study shows that the innovation value of AI in SMEs depends less on adoption itself and more on the organizational and entrepreneurial capabilities that allow firms to learn from AI, act on AI-enabled insights, and transform those insights into innovation. AI does not innovate on behalf of SMEs. Rather, SMEs innovate with AI when they possess the digital maturity, absorptive capacity, and entrepreneurial agility needed to convert AI adoption into innovation-relevant action.

Declarations

Author Contribution

A.Z.K. contributed to conceptualization, theoretical framing, methodology, questionnaire development, data analysis, interpretation of findings, visualization, project administration, and writing the original draft. L.-P.D. contributed to Supervision, theoretical guidance, questionnaire development, critical review, writing – review and editing, and final manuscript approval. M.H.B. contributed to data collection, respondent coordination, data screening support, literature support, and manuscript review. Z.N.K. contributed to data collection, data checking support, literature support, formatting assistance, and manuscript review. All authors reviewed and approved the final manuscript.

Data Availability

The datasets generated and analyzed during the current study are not publicly available because they contain confidential survey responses from SME managers and were collected under assurances of anonymity and confidentiality. Anonymized data may be made available from the corresponding author upon reasonable request and subject to appropriate ethical and confidentiality considerations.

References

1. Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, *13*(1), 333–372. https://doi.org/10.1257/mac.20180386
2. Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152. https://doi.org/10.2307/2393553
3. 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
4. Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers*, *24*, 1709–1734. https://doi.org/10.1007/s10796-021-10186-w
5. European Commission. (2003). Commission Recommendation 2003/361/EC of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises. *Official Journal of the European Union*, *L 124*, 36–41.
6. Flatten, T. C., Engelen, A., Zahra, S. A., & Brettel, M. (2011). A measure of absorptive capacity: Scale development and validation. *European Management Journal*, *29*(2), 98–116. https://doi.org/10.1016/j.emj.2010.11.002
7. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104
8. Gunday, G., Ulusoy, G., Kilic, K., & Alpkan, L. (2011). Effects of innovation types on firm performance. *International Journal of Production Economics*, *133*(2), 662–676. https://doi.org/10.1016/j.ijpe.2011.05.014
9. Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change*, *162*, 120392. https://doi.org/10.1016/j.techfore.2020.120392
10. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.
11. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
12. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*, 115–135. https://doi.org/10.1007/s11747-014-0403-8
13. Karimi, J., & Walter, Z. (2015). The role of dynamic capabilities in responding to digital disruption: A factor-based study of the newspaper industry. *Journal of Management Information Systems*, *32*(1), 39–81. https://doi.org/10.1080/07421222.2015.1029380

14. Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, *11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101
15. Li, L., Su, F., Zhang, W., & Mao, J. Y. (2018). Digital transformation by SME entrepreneurs: A capability perspective. *Information Systems Journal*, *28*(6), 1129–1157. https://doi.org/10.1111/isj.12153
16. Lu, Y., & Ramamurthy, K. (2011). Understanding the link between information technology capability and organizational agility: An empirical examination. *MIS Quarterly*, *35*(4), 931–954. https://doi.org/10.2307/41409967
17. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434
18. Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice*, *41*(6), 1029–1055. https://doi.org/10.1111/etap.12254
19. Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, *48*(8), 103773. https://doi.org/10.1016/j.respol.2019.03.018
20. OECD/Eurostat (2018). *Oslo Manual 2018: Guidelines for collecting, reporting and using data on innovation* (4th ed.). OECD Publishing. https://doi.org/10.1787/9789264304604-en
21. Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
22. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072
23. Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of IT in contemporary firms. *MIS Quarterly*, *27*(2), 237–263. https://doi.org/10.2307/30036530
24. Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189
25. Stanford Institute for Human-Centered Artificial Intelligence (2025). *The AI Index 2025 annual report*. Stanford University.
26. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of sustainable enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350. https://doi.org/10.1002/smj.640
27. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z.

28. 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
29. Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems*, *28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003
30. Wang, C. L., & Ahmed, P. K. (2004). The development and validation of the organisational innovativeness construct using confirmatory factor analysis. *European Journal of Innovation Management*, *7*(4), 303–313. https://doi.org/10.1108/14601060410565056
31. Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, *52*(3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001
32. Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, *27*(2), 185–203. https://doi.org/10.5465/amr.2002.6587995

Figures

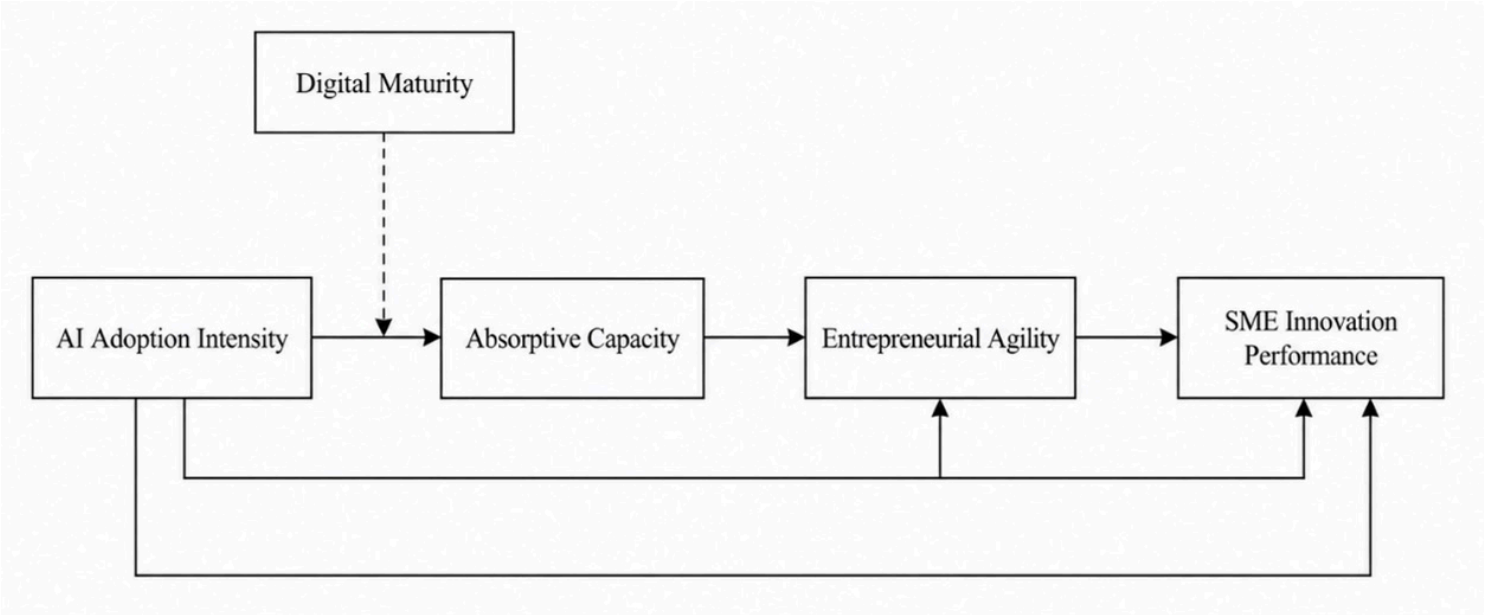


Figure 1

Conceptual model

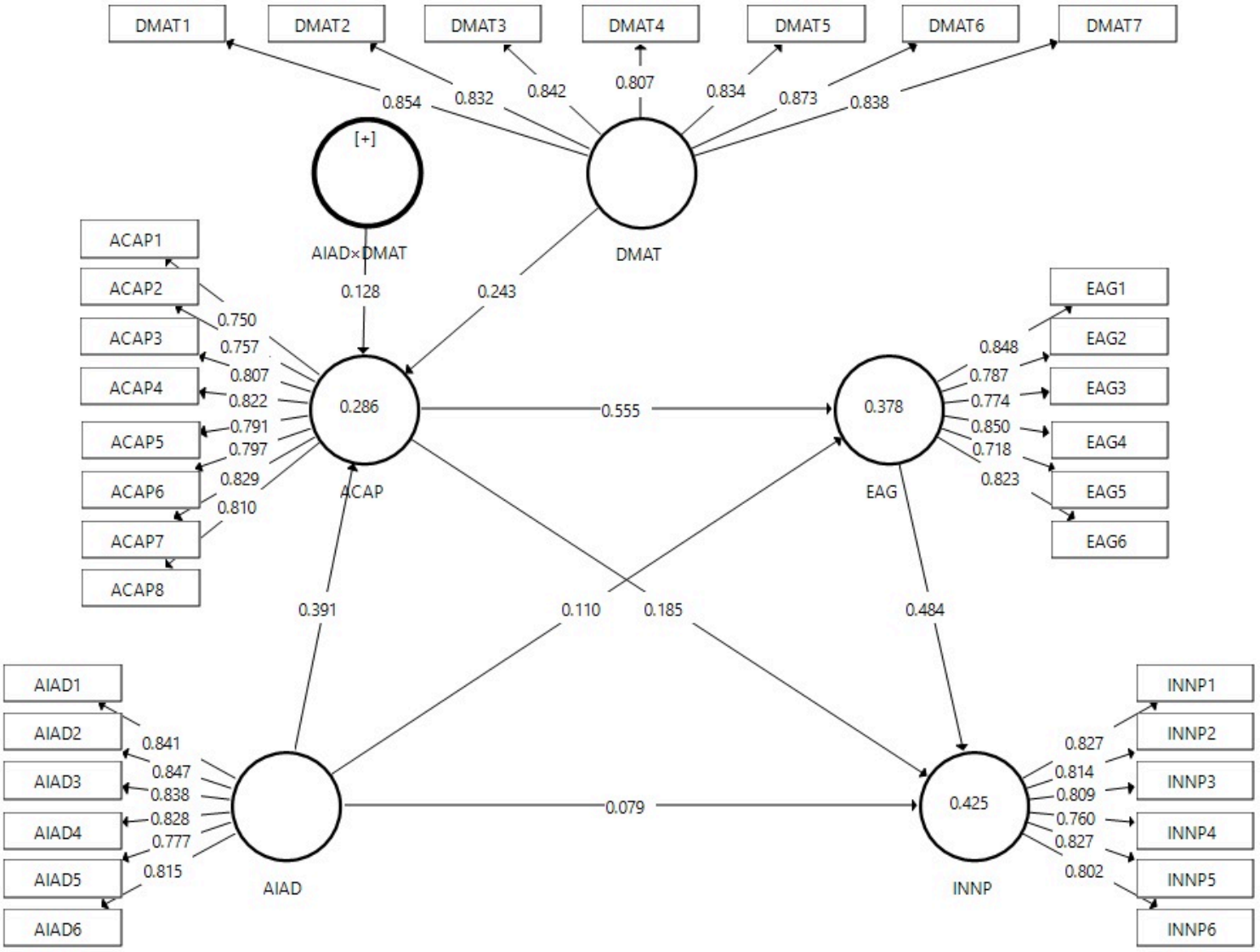


Figure 2

PLS Algorithm results

Note. The figure displays standardized path coefficients, outer loadings, and R² values obtained from the PLS Algorithm.

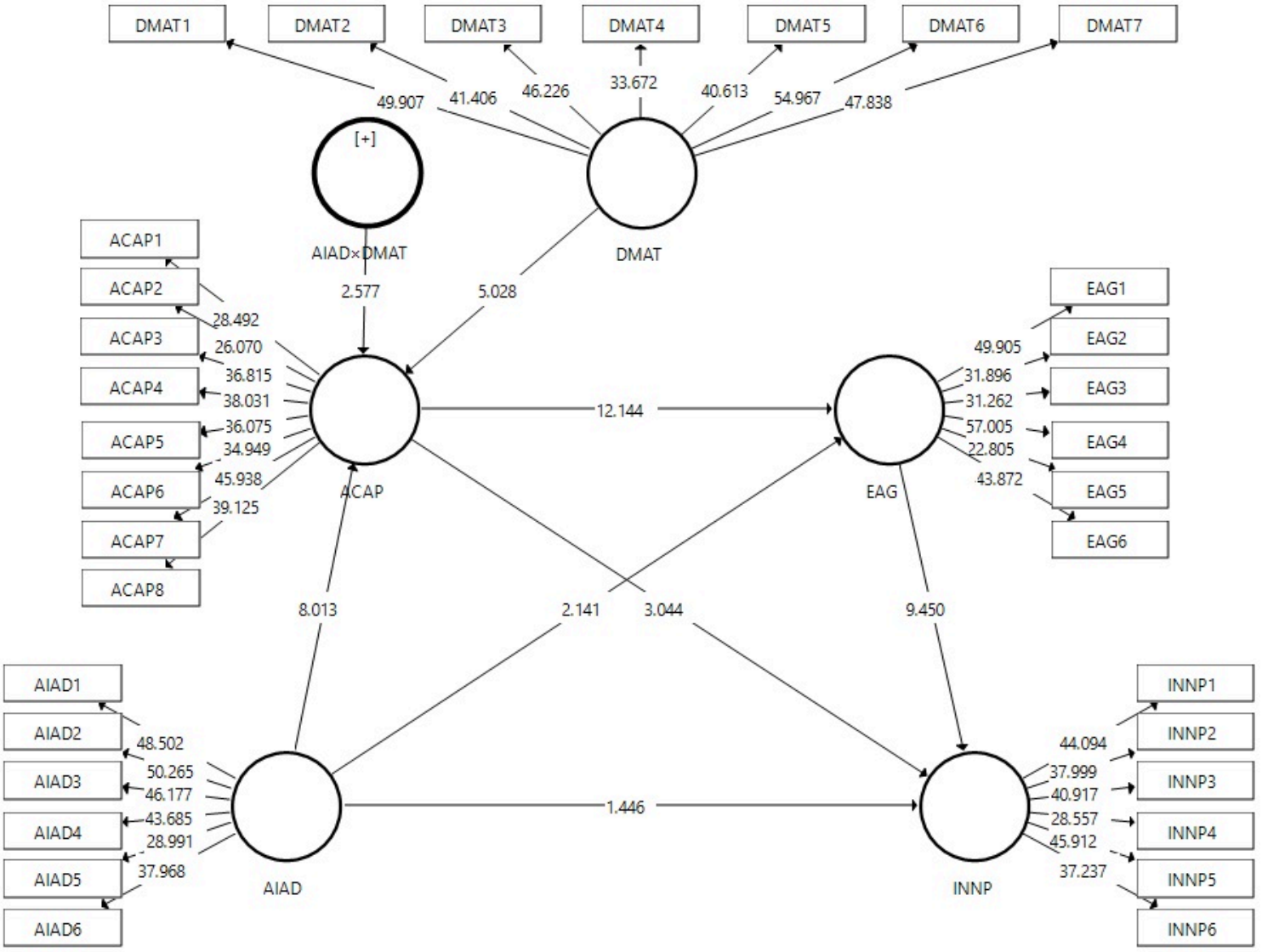


Figure 3

Bootstrapping results

Note. The figure displays bootstrapped t-values for the structural paths based on 5,000 bootstrap subsamples.

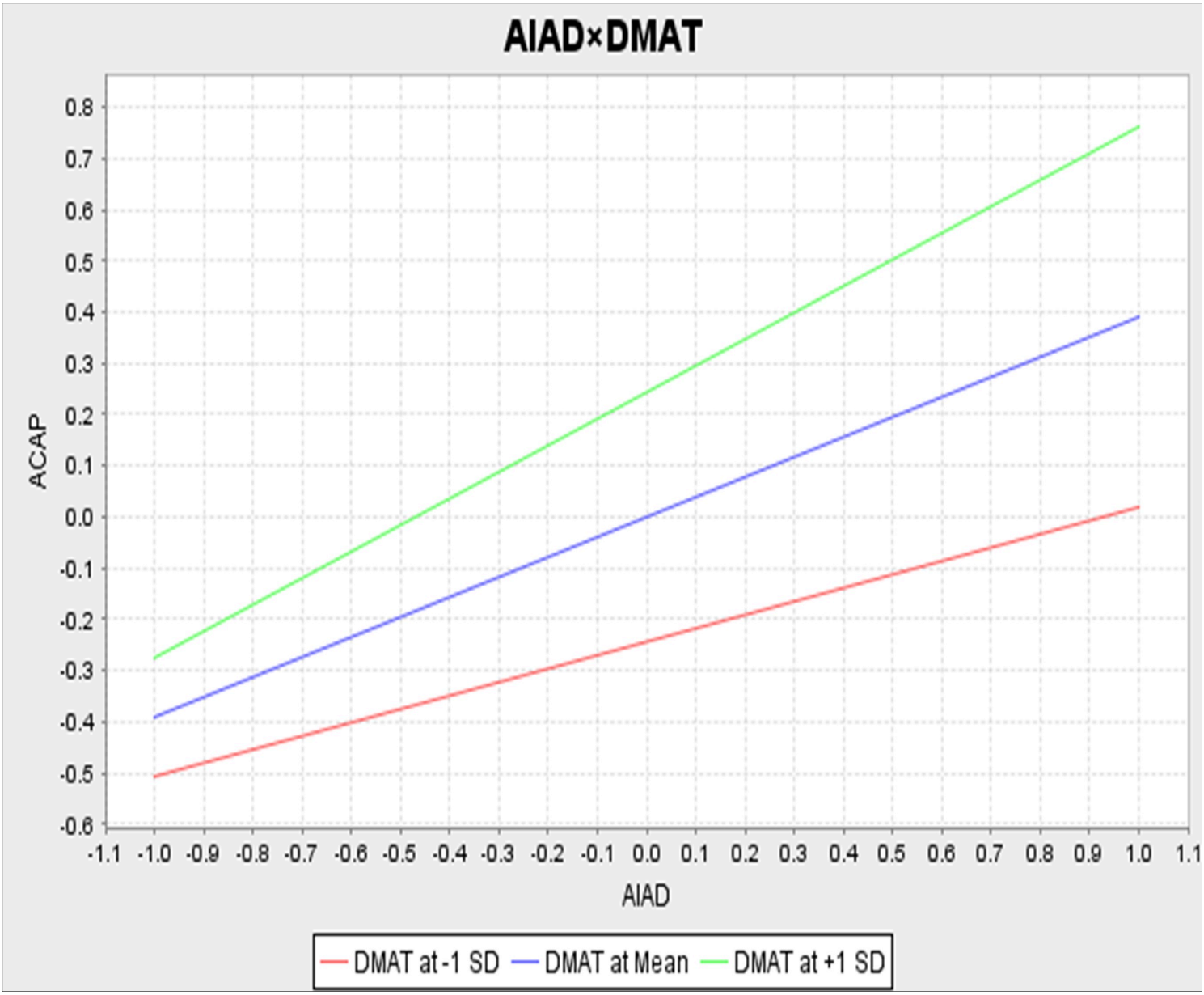


Figure 4

Simple slope analysis of the moderating effect of digital maturity
Note. The figure shows the predicted relationship between AI adoption intensity and absorptive capacity at low, mean, and high levels of digital maturity.

Supplementary Files

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- SupplementaryMaterial.pdf