Turning Artificial Intelligence Readiness into Innovation in Greek Small and Medium-Sized Enterprises

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ABSTRACT

Artificial intelligence (AI) is increasingly accessible to small and medium-sized enterprises (SMEs), yet prior research explains less clearly how readiness is converted into innovation performance after firms move beyond initial tool adoption. This study examines Greek SMEs and tests whether AI readiness influences innovation performance through AI assimilation and organizational learning capability. Using an exploratory sequential mixed-methods design, the study combines 14 semi-structured interviews with survey evidence from 420 valid responses. Partial least squares structural equation modeling is estimated on 257 AI-exposed firms. The findings show that readiness positively affects assimilation, assimilation strengthens organizational learning capability and innovation performance, and the serial mediation pathway is supported. The main contribution is to show that AI readiness creates innovation value when it becomes embedded in organizational routines and converted into learning capability, rather than when firms merely gain access to AI tools.

Keywords: AI readiness, AI assimilation, Organizational learning capability, Innovation performance, SMEs, Greece

1. Introduction

Artificial intelligence has become an important managerial and organizational issue for SMEs. It is increasingly used to support customer service, marketing, analytics, process improvement, content production, decision support, and service innovation. However, the benefits of AI are not created solely by the availability of tools. Firms must have the organizational readiness to use these tools reliably, responsibly, and in an innovation-oriented way. This issue is particularly important for SMEs because they often operate with limited financial resources, limited specialized personnel, informal routines, and strong dependence on owner-manager decisions [1], [2].

The empirical context strengthens the relevance of the study. The European Union has set a 2030 target for more than 90% of SMEs to reach at least a basic level of digital intensity, yet only 53% of Greek SMEs reached that level in 2024, compared with 73% across the European Union [3]. The 2025 Greece Digital Decade country report also indicates that the uptake of digital technologies by

Greek businesses remains a challenge, especially for SMEs [2]. In addition, the OECD identifies connectivity, data, algorithms and compute, skills, and finance as key enablers of AI adoption by SMEs [1]. These conditions make Greece a relevant context for examining whether firms can convert AI readiness into actual innovation performance.

Previous research has advanced understanding of AI adoption, digital transformation, AI capability, organizational learning, and innovation performance in firms [4], [5], [6], [7], [8], [9]. However, important gaps remain. Much of the literature still treats adoption or use intention as the main outcome, even though adoption does not indicate whether AI has been embedded in routines, decisions, workflows, and learning processes. Research also explains less clearly how AI readiness translates into innovation performance in SMEs, especially in digitally uneven European contexts where firms may face stronger constraints on data quality, employee skills, governance, and external support [1], [2], [3]. This study addresses these gaps by examining the conversion process through which AI readiness becomes innovation performance through AI assimilation and organizational learning capability in Greek SMEs.

The focus of this research is therefore not whether Greek SMEs have begun using AI. Instead, the study examines how readiness becomes innovation performance after AI is assimilated into organizational routines and translated into learning capability. AI readiness is defined as the firm's preparedness to use AI through digital infrastructure, data readiness, leadership support, employee AI literacy, responsible governance, and resource availability. AI assimilation refers to the embedding of AI into everyday routines, decision-making, and business functions. Organizational learning capability refers to the firm's ability to learn from technological experimentation, share lessons, convert knowledge into improved routines, and adapt to new opportunities [8], [9]. This focus allows the study to move beyond tool access and explain the organizational process through which AI becomes innovation-relevant in SMEs.

The study also examines two boundary conditions. First, a knowledge-sharing climate is expected to strengthen the relationship between AI assimilation and organizational learning capability. This is because AI outputs become organizational knowledge only when employees and managers exchange interpretations, mistakes, use cases, and lessons learned. Second, external digital support is expected to strengthen the relationship between AI readiness and AI assimilation. This support may come from consultants, vendors, chambers, universities, public programs, or European and national digital innovation initiatives. This is especially relevant for Greek SMEs because many firms may depend on external support to compensate for limited internal digital capacity [2]. The central research question is therefore: *How does AI readiness influence innovation performance in Greek SMEs, and through which organizational learning and assimilation mechanisms does this relationship operate?*

To answer this question, the study uses an exploratory sequential mixed-methods design. The qualitative phase uses semi-structured interviews with Greek small and medium-sized enterprise owners, managers, digital officers, innovation officers, and consultants to refine the contextual understanding and survey instrument. The quantitative phase uses survey data from Greek small and medium-sized enterprise decision-makers and tests the proposed model through partial least squares structural equation modeling.

This study contributes to management and organization research by reframing AI readiness as a perceived organizational capability that combines infrastructure, data readiness, leadership support, employee AI literacy, responsible-use expectations, and resource availability. It also distinguishes AI assimilation from initial adoption and shows that assimilation is the mechanism through which readiness becomes organizationally meaningful. Finally, the study explains AI-enabled innovation through a serial learning pathway in which readiness supports assimilation, assimilation strengthens organizational learning capability, and learning capability improves innovation performance. The findings further show that knowledge-sharing climate and external digital support matter as direct contextual enablers, even though they do not significantly amplify the hypothesized relationships as moderators. This contribution clarifies how AI creates value in SMEs when it is embedded in routines, interpreted through shared learning, and translated into innovation-oriented organizational change.

2. Literature Review

2.1 AI Readiness in SMEs

AI readiness refers to the extent to which a firm has the organizational conditions required to use AI productively, responsibly, and repeatedly. In SMEs, AI readiness cannot be reduced to the availability of digital tools or managerial interest in new technologies. It includes digital infrastructure, usable data, leadership commitment, employee AI literacy, resource availability, and responsible governance practices. This broader view is necessary because SMEs often face constraints in finance, skills, formal routines, and specialized digital expertise [1], [4], [5], [6].

Recent research on AI adoption in SMEs indicates that internal capabilities are essential for moving from awareness to actual use. Digital innovation and organizational capabilities determine whether firms can adopt and benefit from AI [4]. Similarly, AI readiness models designed for SMEs emphasize strategic, organizational, technological, capability, and ecosystem readiness [5]. These arguments suggest that AI readiness is not a single technological condition. It is a bundle of organizational capabilities that enables firms to recognize AI opportunities, evaluate risks, allocate resources, and prepare employees for new ways of working.

The Greek context increases the relevance of this issue. Greek SMEs operate in a European policy environment that encourages digital transformation, yet many firms continue to face uneven digital maturity and limited adoption of advanced technologies [2], [3]. Therefore, the main problem is not simply whether Greek SMEs are aware of AI. The more important question is whether they possess the readiness conditions to assimilate AI into routines and achieve innovation-oriented outcomes.

Dynamic capabilities theory helps explain this relationship. Firms create value in changing environments when they sense opportunities, seize them through organizational action, and reconfigure resources and routines [10]. AI readiness supports this process by giving firms the infrastructure, knowledge, leadership support, and governance routines needed to move from

technological possibility to organizational use. Therefore, the following hypothesis is proposed:
H1. AI readiness positively influences AI assimilation in Greek SMEs.

2.2 AI Assimilation in Organizational Routines

AI assimilation differs from AI adoption. Adoption refers to the initial decision to use AI tools. Assimilation refers to the extent to which AI becomes embedded in everyday routines, decisions, workflows, and business functions. This distinction is important because many firms experiment with AI without changing their operations. For example, an SME may use generative AI occasionally for marketing content, but this does not necessarily mean that AI has become part of its decision-making, customer service, operations, or innovation routines.

The distinction between adoption and assimilation is especially important in SMEs because technology use may depend heavily on the owner-manager or a small number of digitally capable employees. In such firms, AI use can remain individualized, informal, and weakly connected to organizational learning. Assimilation requires a deeper form of use. It occurs when AI-supported tools are incorporated into processes such as customer analysis, forecasting, service design, training, inventory management, financial planning, or process improvement.

Prior digital transformation literature shows that digital technologies create value only when they are integrated into organizational processes, business models, and managerial routines [11], [12]. This logic applies directly to AI. AI readiness may create the conditions for adoption, but assimilation is the mechanism through which readiness becomes operationally meaningful. When AI tools are embedded in work routines, employees and managers are more likely to generate new information, test alternative decisions, and identify improvement opportunities.

AI assimilation may also directly influence innovation performance. Firms that use AI in daily routines may improve service delivery, reduce inefficiencies, develop new customer insights, or redesign internal processes. However, this study argues that AI assimilation is also important because it strengthens organizational learning capability. Embedded AI use exposes firms to new information, new errors, new interpretations, and new possibilities for experimentation. Therefore, the following hypotheses are proposed:
H2. AI assimilation positively influences organizational learning capability.
H3. AI assimilation positively influences innovation performance.

2.3 Organizational Learning Capability

Organizational learning capability refers to a firm's ability to acquire, share, interpret, and apply knowledge to improve adaptation and performance. In the context of AI, organizational learning capability is essential because AI outputs do not automatically become useful organizational knowledge. Employees and managers must evaluate AI-generated information, compare it with experience, discuss errors, identify useful patterns, and translate insights into improved routines.

The knowledge-based view of the firm provides a theoretical basis for this argument. It treats knowledge as a critical organizational resource and emphasizes the firm's role in integrating specialized knowledge into productive activity [13]. AI can increase the amount of information available to firms, but the value of that information depends on whether the firm can interpret and use it. Without learning capability, AI outputs may remain isolated, misunderstood, or underused.

Organizational learning capability has been widely linked to experimentation, managerial commitment, knowledge transfer, and openness to new ideas [14]. These dimensions are directly relevant to AI assimilation. Firms that use AI in everyday operations must learn to evaluate outputs, avoid overreliance, protect data, revise work practices, and adapt decision-making. This is not only a technical process. It is a learning process that requires managerial support, employee involvement, and cross-functional knowledge exchange.

Organizational learning capability is also expected to influence innovation performance. Learning enables firms to transform technological experience into improved products, services, processes, customer experiences, and business models [15]. AI may provide new inputs for innovation, but learning capability determines whether these inputs are absorbed and applied. This is consistent with absorptive capacity research, which argues that firms benefit from external and new knowledge when they can recognize, assimilate, transform, and exploit it [16], [17]. Knowledge creation research similarly shows that organizational value depends on the conversion and circulation of knowledge across individual and collective levels [18].

Recent research also supports the connection between AI, learning, and innovation outcomes [8], [9]. However, this study extends this logic by examining whether organizational learning capability mediates the relationship between AI assimilation and innovation performance in Greek SMEs. This is important because it explains why AI use may produce different results across firms with similar access to tools. Therefore, the following hypotheses are proposed:

H4. Organizational learning capability positively influences innovation performance.

H5. AI assimilation and organizational learning capability mediate the relationship between AI readiness and innovation performance in a serial manner.

2.4 Knowledge-Sharing Climate and External Digital Support

Knowledge-sharing climate refers to the extent to which employees and managers exchange useful knowledge, practical experience, mistakes, and lessons. This construct is important because AI assimilation may remain fragmented if employees use AI tools individually without sharing what they learn. In SMEs, where formal knowledge management systems may be limited, knowledge sharing often depends on interpersonal trust, managerial encouragement, and informal routines.

A strong knowledge-sharing climate should strengthen the relationship between AI assimilation and organizational learning capability. When employees discuss AI use, compare outputs, share prompts, explain errors, and transfer useful practices, AI assimilation becomes a collective learning process. When knowledge sharing is weak, AI-related learning may remain locked within individuals or departments. This limits the firm’s ability to convert AI use into organizational knowledge. The knowledge management literature supports this logic by treating knowledge sharing and integration as organizational capability conditions [19], leading to the following hypothesis:

H6. Knowledge-sharing climate strengthens the relationship between AI assimilation and organizational learning capability.

External digital support is also relevant to AI assimilation in SMEs. External support may come from consultants, vendors, chambers of commerce, universities, training providers, public funding schemes, sectoral associations, European Digital Innovation Hubs, or national digital innovation initiatives. This support is especially important for SMEs because they may lack internal AI specialists, formal data teams, or dedicated digital transformation departments.

However, external support should not be treated as a substitute for internal readiness. Firms with stronger internal readiness are more likely to understand, absorb, and apply external support. Firms with weak internal readiness may receive training, advice, or funding but still struggle to embed AI into routines. This means external digital support is best conceptualized as a moderator. It strengthens the effect of AI readiness on AI assimilation when firms have enough internal capacity to use external resources productively.

This logic is consistent with the technology-organization-environment perspective, which argues that technology adoption depends on technological, organizational, and environmental conditions [20], [21]. In this study, AI readiness represents the internal organizational condition, while external digital support represents the environmental condition that may strengthen the transition from readiness to assimilation. Therefore, the following hypothesis is proposed:

H7. External digital support strengthens the relationship between AI readiness and AI assimilation.

Figure 1 presents the conceptual model, which positions AI readiness as the main antecedent of AI assimilation, AI assimilation as the mechanism through which readiness becomes embedded in organizational routines, and organizational learning capability as the learning mechanism through which AI-supported activity contributes to innovation performance. The model also includes a direct path from AI readiness to innovation performance, the direct main effects required for the two moderation tests, and the two hypothesized interaction effects. A knowledge-sharing climate is modeled as a direct predictor of organizational learning capability and as a moderator of the relationship between AI assimilation and organizational learning capability. External digital support is modeled as a direct predictor of AI assimilation and as a moderator of the relationship between AI readiness and AI assimilation.

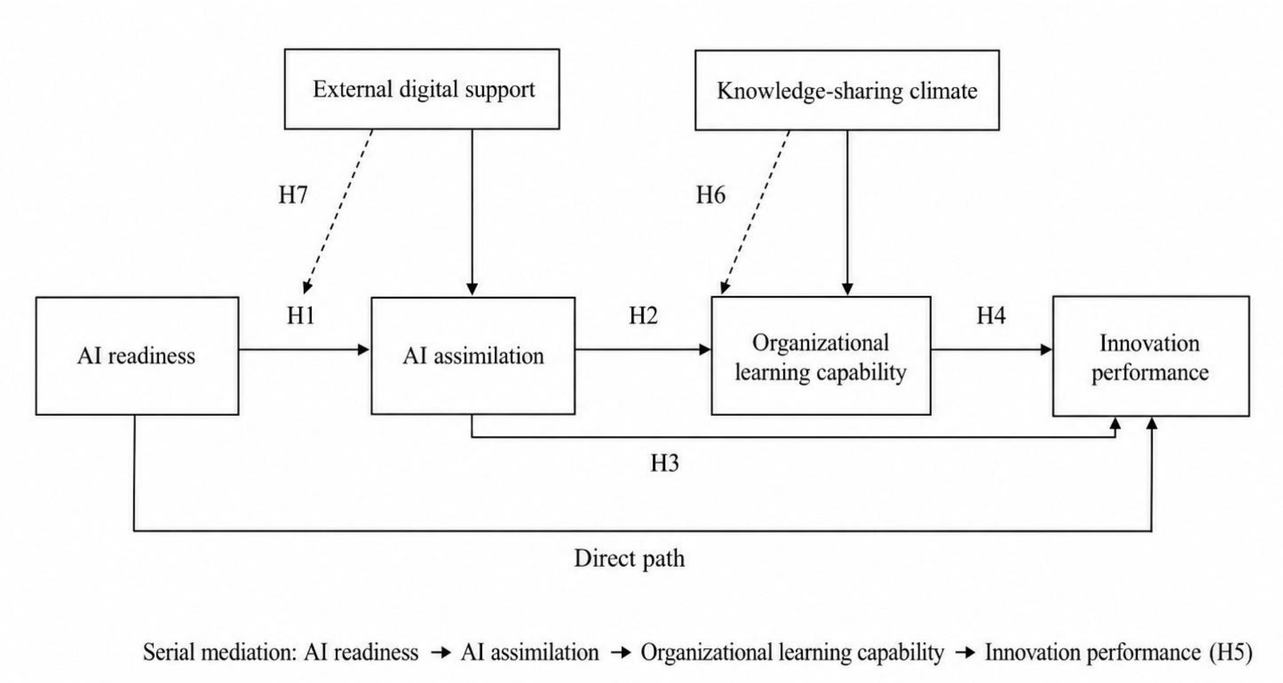

Figure 1. Conceptual model
Source: By author.

2.5 Innovation Performance in SMEs

Innovation performance refers to the extent to which a firm introduces new or improved products, services, processes, customer experiences, organizational practices, or business models. This broad definition is appropriate for SMEs because innovation in smaller firms is often incremental, practical, and market-facing. It may not appear through patents or formal research and development outputs, but through service improvement, customer adaptation, process redesign, new delivery models, and operational changes.

AI can contribute to innovation performance by improving information processing, identifying customer patterns, supporting forecasting, accelerating experimentation, automating routine work, and helping firms generate new ideas. However, this study argues that AI does not automatically create innovation performance. Its effect depends on whether the firm is ready to use AI, whether AI becomes assimilated into organizational routines, and whether the firm can transform AI-supported experience into organizational learning.

Recent research on digital transformation and AI in SMEs similarly shows that technology-enabled innovation depends on dynamic capabilities, digital culture, adoption depth, sustainable growth conditions, digital awareness, strategic roadmapping, implementation capability, and continuous improvement rather than isolated tool use [22], [23], [24], [25]. This argument clarifies the study's contribution. Prior research has examined AI adoption, digital transformation, organizational learning, and innovation performance. However, less attention has been given to the mechanisms by which AI readiness translates into innovation performance in digitally uneven SME contexts.

This model extends prior research by shifting attention from AI adoption as an endpoint to AI assimilation and organizational learning as mechanisms through which readiness becomes innovation performance. It positions the Greek SME context as a useful setting for examining how digitally uneven firms attempt to transform AI-related preparedness into practical innovation outcomes.

3. Research Design

3.1 Research Context and Design

This study examines how AI readiness influences innovation performance in Greek SMEs. Greece provides an appropriate empirical context because SMEs are central to the national economy, but their digital maturity and advanced technology use remain uneven compared with more digitally advanced European economies [1], [2], [3]. The study focuses on SMEs because their AI adoption decisions are usually shaped by resource constraints, owner-manager influence, limited specialized personnel, dependence on external support, and informal learning routines. These characteristics make Greek SMEs a useful context for examining how AI readiness is converted into AI assimilation, organizational learning capability, and innovation performance.

The study used an exploratory sequential mixed-methods design. The first phase consisted of semi-structured interviews with Greek SME owners, managers, digital transformation officers, innovation officers, and consultants who worked with SMEs. This phase contextualized the conceptual model, identified Greece-specific barriers and enablers, and refined the wording of the survey instrument. The second phase consisted of a structured survey of Greek SME decision-makers. This phase tested the hypothesized relationships among AI readiness, AI assimilation, organizational learning capability, knowledge-sharing climate, external digital support, and innovation performance.

The exploratory sequential design is appropriate because AI readiness remains an emerging organizational issue in SMEs and requires contextual interpretation before survey testing. The qualitative phase captured practical meanings, barriers, and enabling conditions in Greek SMEs, while the quantitative phase tested the proposed direct, mediating, and moderating relationships. Combining interview and survey evidence strengthens the study by allowing the statistical findings to be interpreted in relation to the managerial realities of Greek SMEs.

3.2 Qualitative Phase

The qualitative phase consisted of 14 semi-structured interviews with Greek SME owners, managers, digital transformation officers, innovation officers, and consultants supporting SME digital transformation. Participants were selected purposively because they had direct knowledge of SME digitalization, AI use, innovation activities, or technology-related decision-making. The interviewees included SME owners, general managers, operations managers, digital transformation managers, innovation managers, and external digitalization consultants, representing firms or advisory experience across manufacturing, retail, tourism and hospitality, professional services, logistics, information technology, and agrifood sectors. The interview group included four SME owners, three general managers, two operations managers, two digital or innovation managers, and three external digitalization consultants, providing perspectives from both internal decision-makers and external support actors.

The interviews were conducted between January 2025 and February 2025. Each interview lasted approximately 40 to 75 minutes and explored current digital tool use, AI experimentation or adoption, data availability and quality, employee AI literacy, leadership support, responsible AI practices, external digital support, and perceived innovation outcomes. The interviews were conducted both online and in person, and participants were informed of the study's purpose, confidentiality, voluntary participation, and their right to withdraw.

Interview data were analyzed thematically through an iterative coding process. The analysis began with familiarization with the interview notes or transcripts. Initial codes were developed around AI readiness, AI assimilation, organizational learning, innovation, knowledge sharing, and external support. Codes were then compared across participants to identify recurring themes and sector-specific differences. The qualitative phase was not used to test the hypotheses directly. Instead, it was used to refine the survey wording, verify the constructs' contextual relevance, and interpret the quantitative findings in relation to the managerial realities of Greek SMEs. The final two interviews did not yield new first-order codes, indicating sufficient thematic saturation for instrument refinement and contextual interpretation.

3.3 Quantitative Phase and Sampling

The quantitative phase used a cross-sectional survey of Greek SMEs operating in sectors where AI and digital transformation have practical relevance, including tourism and hospitality, retail and e-commerce, professional services, education and training, manufacturing, logistics, food and beverage, and business services. The target respondents were individuals with sufficient knowledge of the firm's digital practices and innovation activities, including owners, general managers, department managers, human resource managers, operations managers, digital or information technology managers, and senior employees involved in technology-related decisions.

The survey was administered via Google Forms from March 2025 to June 2025. Respondents were recruited through SME networks, chambers of commerce, professional associations, LinkedIn, and direct email invitations. The questionnaire was distributed in both Greek and English. When Greek was used, the English master questionnaire was translated into Greek and back-translated into English to reduce semantic inconsistency.

The survey generated 470 attempted responses. After eligibility and data-quality screening, 420 valid responses from Greek SMEs were retained for sample description. Responses were excluded when the respondent did not work in a Greek SME, lacked sufficient knowledge of the firm's digital or AI practices, provided incomplete answers, failed attention checks, reported non-Greek operations, represented a large or linked enterprise, or showed duplicate or low-quality response patterns.

The full clean sample was used to describe the respondent and firm profile. The main structural model was estimated on the AI-exposed subsample of 257 firms because AI assimilation is theoretically meaningful only for firms that reported at least informal AI experimentation. Firms reporting no AI use were retained for descriptive comparison but excluded from the main structural model involving AI assimilation. A stricter robustness check was also conducted on the formal AI-user subsample of 102 firms, although this subgroup was interpreted cautiously because only four firms reported AI embedded across core operations. The AI-exposed sample was deemed adequate for the PLS-SEM analysis because it exceeded the common minimum sample recommendations for models with multiple predictors, mediation paths, and interaction terms [26], [27]. The formal-AI-user subsample was therefore used solely as a stricter sensitivity check rather than as the primary sample for model estimation.

The survey included screening questions, firm profile questions, construct measurement items, and control variables. Screening questions confirmed that the firm operated in Greece, had fewer than 250 employees, and that the respondent had sufficient knowledge of the firm's digital or AI-related practices. Firm profile questions captured sector, firm age, firm size, region, export activity, AI-use status, and main AI-use area. Control variables included firm size, firm age, sector, export activity, region, respondent role, AI-use status, and prior digital transformation experience.

3.4 Measurement Development

The questionnaire used a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The English version served as the master instrument. Respondents could complete either the Greek or English version. The Greek version was translated from English and then back-translated into English to reduce semantic inconsistency before distribution.

AI readiness is measured as a multidimensional construct that captures digital infrastructure, data readiness, leadership support, employee AI literacy, responsible AI governance, and resource availability. AI assimilation measures the extent to which AI tools are embedded in everyday routines, decision-making processes, work practices, and business functions. Organizational learning capability measures the firm's ability to learn from technological experimentation, share lessons, convert knowledge into routines, and adapt to new opportunities [14]. Knowledge-sharing climate measures the extent to which employees and managers exchange useful knowledge about digital and AI-related practices. External digital support measures the degree of support received from consultants, vendors, public programs, universities, sectoral associations, chambers, and European or national digital innovation initiatives. Innovation performance measures new or improved products, services, processes, customer experiences, organizational practices, and business models.

Table 1 summarizes the constructs, definitions, measurement items, and source logic used to develop the questionnaire, which included construct-specific items measured on a seven-point Likert scale, with wording adapted to the Greek SME context after the qualitative phase and pilot test.

Table 1. Constructs, definitions, measurement items, and sources

Construct	Operational definition	Items	Source logic
AI readiness	The extent to which the firm has the infrastructure, data readiness, leadership support, employee AI literacy, responsible-use expectations, and resources needed to use AI	10	Adapted from SME AI adoption, AI capability, and AI readiness literature emphasizing digital infrastructure, data, skills, governance, managerial commitment, and organizational

Construct	Operational definition	Items	Source logic
	productively.		resources [1], [5], [6].
AI assimilation	The extent to which AI tools are embedded in daily routines, decisions, workflows, and business functions rather than used only experimentally or individually.	5	Adapted from IT assimilation and digital transformation research that distinguishes initial adoption from embedded organizational use [4], [11], [12].
Organizational learning capability	The firm’s ability to learn from technological experimentation, share lessons, convert knowledge into improved routines, and adapt to new opportunities.	6	Adapted from organizational learning capability and knowledge-based theory, especially work on learning orientation, knowledge transfer, experimentation, and knowledge integration [13], [14], [15].
Knowledge-sharing climate	The extent to which employees and managers exchange useful knowledge, practical experience, mistakes, and lessons about digital and AI-related work.	5	Adapted from knowledge management capability literature that treats knowledge sharing as an organizational capability condition [19].
External digital support	The degree to which the firm receives useful support from consultants, vendors, public programs, universities, sectoral associations, chambers, or European and national digital innovation initiatives.	5	Adapted from the technology-organization-environment perspective and SME digital ecosystem literature, with emphasis on external support for firms with limited internal digital resources [2], [20].
Innovation performance	The extent to which the firm has introduced new or improved products, services, processes, customer experiences, organizational practices, or business models.	6	Adapted from innovation capability and innovation performance literature linking learning, AI use, firm growth, and product or process innovation [8], [9], [15].
Control variables	Firm and respondent characteristics that may influence AI assimilation, organizational learning, or innovation performance.	8	Included to reduce alternative explanations related to organizational scale, age, sector, region, export activity, respondent role, AI-use status, and prior digital transformation experience.

Source: By author.

All main constructs were modeled as reflective constructs because the items were expected to represent observable manifestations of the same underlying latent variable. This choice was appropriate because the research objective was to examine relationships among perceived organizational capabilities, AI assimilation, learning conditions, and innovation outcomes rather than to construct a formative index of firm-level AI readiness. The measurement items were reviewed for conceptual clarity, contextual relevance, and consistency with prior literature before the main data collection. A pilot test with 15 Greek SME respondents was conducted to identify unclear wording, excessive length, misunderstood terms, or response fatigue. Feedback from the pilot test was used to refine the questionnaire before the main survey was distributed.

3.5 Ethical and Procedural Safeguards

Participation was voluntary. All participants received information about the study's purpose, the type of data collected, the estimated time required, and their right to withdraw before submitting their responses. No personally identifying information was reported in the manuscript. Interview participants were assigned codes, and survey responses were analyzed in aggregate form. The study did not collect sensitive personal data. Firm-level information was reported only in categories, such as sector, firm size, and region, to reduce identifiability.

Several procedural safeguards were used to reduce common method bias. Respondents were informed that there were no right or wrong answers. The questionnaire separated predictor, mediator, moderator, and outcome constructs into different sections. Items were written clearly and neutrally to reduce ambiguity. The survey included both screening and attention checks. Statistical checks were also conducted after data collection to assess whether common method variance threatened the validity of the results [28].

3.6 Data Analysis Procedure

The quantitative data were analyzed using partial least squares structural equation modeling in SmartPLS 4. This approach was suitable for the study because the conceptual model was prediction-oriented, included multiple latent constructs, and tested mediation and moderation. It was also appropriate for examining complex relationships among organizational capabilities, technology assimilation, learning, and innovation outcomes [26].

The analysis proceeded in four stages. First, the data were screened for missing values, invalid responses, outliers, normality, and careless response patterns. Descriptive statistics were then reported for the sample profile and the main constructs. Second, the measurement model was assessed. Indicator loadings, Cronbach's alpha, composite reliability, and average variance extracted were used to evaluate reliability and convergent validity. Discriminant validity was assessed using the heterotrait-monotrait ratio and, where appropriate, the Fornell-Larcker criterion [29], [30]. Multicollinearity was assessed through variance inflation factors.

Third, the structural model was tested. Path coefficients, t-values, p-values, confidence intervals, coefficients of determination, effect sizes, and predictive relevance were reported. The direct relationships from AI readiness to AI assimilation, from AI assimilation to organizational learning capability, from organizational learning capability to innovation performance, from AI assimilation to innovation performance, and from AI readiness to innovation performance were examined. The direct path from AI readiness to innovation performance was included to determine whether the mediation mechanism was partial or full.

Fourth, mediation and moderation were tested through bootstrapping with 5,000 subsamples. The serial mediation analysis examined whether AI readiness influenced innovation performance through AI assimilation and organizational learning capability. The moderation analysis examined whether knowledge-sharing climate strengthened the relationship between AI assimilation and organizational learning capability, and whether external digital support strengthened the relationship between AI readiness and AI assimilation.

The qualitative and quantitative findings were integrated in the Results and Discussion section. Interview evidence was used to interpret the statistical results, especially where the findings revealed strong, weak, or non-significant relationships. This integration helped explain whether Greek SMEs converted AI readiness into innovation performance through internal learning processes, external support mechanisms, or both.

4. Results and Discussion

4.1 Sample Profile and Data Screening

The final dataset included 420 valid responses from Greek SMEs, after 50 attempted responses were excluded according to predefined eligibility and data-quality criteria. The retained sample included 151 micro firms, 190 small firms, and 79 medium-sized firms. The largest sector groups were tourism and hospitality, retail and e-commerce, professional services, food and beverage, business services, manufacturing, education and training, and logistics. Attica and Central Macedonia accounted for the largest regional shares, consistent with their economic weight, but this also means the sample is not nationally representative.

Table 2 presents the sample profile. The full sample was used to describe respondent and firm characteristics. However, the main structural model was estimated using the AI-exposed subsample because AI assimilation is theoretically meaningful only for firms that reported at least informal AI experimentation. Firms reporting no AI use were retained for descriptive comparison but excluded from the main model involving AI assimilation.

Table 2. Sample profile

Category	Group	n	%
Firm size	Micro	151	36.0
Firm size	Small	190	45.2
Firm size	Medium	79	18.8
AI-use status	No use	163	38.8
AI-use status	Informal experimentation	155	36.9
AI-use status	Use in one function	75	17.9
AI-use status	Use in several functions	23	5.5
AI-use status	Embedded across core operations	4	1.0
Formal AI user	Yes	102	24.3
Formal AI user	No	318	75.7
Basic digital intensity	Yes	228	54.3
Basic digital intensity	No	192	45.7

Category	Group	n	%
Main sectors	Tourism and hospitality	81	19.3
Main sectors	Retail and e-commerce	56	13.3
Main sectors	Professional services	50	11.9
Main sectors	Food and beverage	47	11.2
Main sectors	Business services	45	10.7
Main sectors	Manufacturing	40	9.5
Main sectors	Education and training	36	8.6
Main sectors	Logistics	33	7.9
Main regions	Attica	147	35.0
Main regions	Central Macedonia	73	17.4
Main regions	South Aegean	31	7.4
Main regions	Crete	27	6.4
Main regions	Thessaly	25	6.0

Source: By author.

The exclusion log showed that the 50 removed responses were excluded for mutually exclusive reasons, including insufficient respondent knowledge, large or linked enterprise status, non-Greek operations, attention-check failure, incomplete responses, and duplicate or low-quality patterns. The cleaned analytical file contained no invalid Likert-scale values outside the expected 1 to 7 range. Missing values were addressed before construct-score calculation, and the final analytical file contained no missing values in the core measurement items.

4.2 Qualitative Findings

The qualitative phase produced six recurring themes: data quality, owner-manager influence, employee AI literacy, external support, learning routines, and innovation outputs. These themes confirmed the relevance of the conceptual model and helped interpret the quantitative findings. Participants indicated that AI use in Greek SMEs depends not only on access to tools, but also on whether firms have reliable data, leadership support, practical employee training, and routines for converting experimentation into shared learning.

Data quality emerged as a central readiness barrier. Several participants indicated that SMEs often collect useful customer, operational, or financial information, but this information is fragmented across spreadsheets, software platforms, or informal records. This limits the firm's ability to use AI for reliable decision-making. Owner-manager influence also appeared repeatedly because AI experimentation in SMEs frequently depends on whether senior leaders allocate time, tolerate trial and error, and encourage employees to test new practices.

Employee AI literacy was another important condition. Participants suggested that employees may be able to use simple AI tools but may lack the ability to verify outputs, protect sensitive information, or apply AI-supported results to operational decisions. External support was considered useful, but interview evidence also suggested that such support is uneven. Consultants, vendors, chambers, universities, and public initiatives can help firms identify AI opportunities, but generic advice does not automatically become operational change.

The learning-routines theme explained why AI assimilation does not automatically produce innovation. AI became more valuable when employees discussed outputs, shared practical examples, corrected errors, and translated lessons into routines. Innovation outputs were mostly incremental, including improvements in service speed, customer response time, scheduling, marketing, and forecasting, as well as process redesign. These findings support the study's decision to measure innovation performance broadly rather than only through patents or formal research and development outputs.

4.3 Measurement Model Assessment

The measurement model was assessed before testing the structural model. The analysis used the AI-exposed subsample of 257 firms. Indicator loadings, Cronbach's alpha, composite reliability, and average variance extracted were used to assess reliability and convergent validity. Discriminant validity was assessed using the heterotrait-monotrait ratio. Multicollinearity was assessed through variance inflation factors.

Table 3 presents the measurement model results. Cronbach's alpha values ranged from 0.800 to 0.897, composite reliability values ranged from 0.862 to 0.916, and average variance extracted values ranged from 0.521 to 0.582. All constructs, therefore, met the minimum reliability and convergent validity requirements. The loading ranges were also acceptable, with the lowest reported loading of 0.682 and the highest of 0.796.

Table 3. Measurement model results, AI-exposed sample

Construct	Items	Cronbach's alpha	Composite reliability	AVE	Loading range	Decision
AI readiness	10	0.897	0.916	0.521	0.682-0.791	Acceptable
AI assimilation	5	0.806	0.865	0.563	0.726-0.773	Acceptable
Organizational learning capability	6	0.832	0.877	0.544	0.717-0.775	Acceptable
Knowledge-sharing climate	5	0.800	0.862	0.556	0.718-0.772	Acceptable
External digital support	5	0.820	0.874	0.582	0.735-0.788	Acceptable
Innovation performance	6	0.848	0.888	0.570	0.714-0.796	Acceptable

Source: By author.

Table 4 presents the HTMT discriminant validity matrix. All HTMT values were below 0.60, with the highest value observed between AI readiness and AI assimilation. These results indicate that the constructs captured distinct conceptual domains and support the separation of AI readiness, AI assimilation, organizational learning capability, knowledge-sharing climate, external digital support, and innovation performance.

Table 4. HTMT discriminant validity matrix, AI-exposed sample

Construct	AIR	AIA	OLC	KSC	EDS	INP
AIR	1.000					
AIA	0.588	1.000				
OLC	0.331	0.509	1.000			
KSC	0.132	0.210	0.342	1.000		
EDS	0.100	0.251	0.127	0.095	1.000	
INP	0.446	0.459	0.454	0.198	0.128	1.000

Source: By author.

Common method bias and multicollinearity were also assessed. Procedurally, the questionnaire separated predictor, mediator, moderator, and outcome constructs, used neutral wording, and assured respondents that there were no right or wrong answers. Statistically, the full collinearity and inner variance inflation factor values were examined. The highest variance inflation factor was 2.84, which was below the recommended threshold of 3.3. These results indicate that common method bias and multicollinearity did not materially threaten the interpretation of the structural model. In addition, the structural model reported effect sizes and predictive relevance. The strongest effect size was observed for the path from AI readiness to AI assimilation ($f^2 = 0.41$), while the Q^2 values for AI assimilation (0.29), organizational learning capability (0.24), and innovation performance (0.31) supported the model's predictive relevance.

4.4 Structural Model Results

Table 5 presents the structural model results. The model explained 28.9% of the variance in AI assimilation, 22.4% in organizational learning capability, and 24.8% in innovation performance. These values are acceptable for an applied management study examining organizational capabilities, learning, and innovation outcomes in SMEs.

Table 5. Structural model results, AI-exposed sample

Hypothesis/path	Relationship	β	t	p	95% CI	R^2 target	Decision
H1	AI readiness -> AI assimilation	0.495	9.324	< .001	[0.394, 0.582]	0.289	Supported
Model path	External digital support	0.171	3.187	.002	[0.065, 0.272]	0.289	Significant

Hypothesis/path	Relationship	β	t	p	95% CI	R^2 target	Decision
	-> AI assimilation						
H7	AI readiness x external digital support -> AI assimilation	0.077	1.433	.153	[-0.046, 0.180]	0.289	Not supported
H2	AI assimilation -> Organizational learning capability	0.380	6.747	< .001	[0.262, 0.487]	0.224	Supported
Model path	Knowledge-sharing climate -> Organizational learning capability	0.217	3.856	< .001	[0.098, 0.332]	0.224	Significant
H6	AI assimilation x knowledge-sharing climate -> Organizational learning capability	0.045	0.809	.419	[-0.067, 0.151]	0.224	Not supported
H4	Organizational learning capability -> Innovation performance	0.250	4.149	< .001	[0.119, 0.375]	0.248	Supported
H3	AI assimilation -> Innovation performance	0.155	2.319	.021	[0.024, 0.295]	0.248	Supported
Model path	AI readiness -	0.240	3.790	< .001	[0.112,	0.248	Significant

Hypothesis/path	Relationship	β	t	p	95% CI	R^2 target	Decision
	> Innovation performance				0.360]		

Source: By author.

H1 was supported. AI readiness had a positive effect on AI assimilation. This indicates that Greek SMEs with stronger digital infrastructure, usable data, leadership support, employee AI literacy, clear governance expectations, and sufficient resources were more likely to embed AI into their routines and business functions. This finding confirms that AI use in SMEs is not only a matter of tool access. It depends on broader organizational preparedness.

H2 was supported. AI assimilation had a positive effect on organizational learning capability. This suggests that when AI tools become part of routines, decisions, and work practices, firms create more opportunities to learn from technological experimentation. AI assimilation exposes employees and managers to new information, errors, interpretations, and improvement opportunities that can be translated into organizational learning.

H3 was supported. AI assimilation had a positive direct effect on innovation performance. This indicates that embedded AI use may directly improve products, services, processes, customer experience, and business practices. The effect was weaker than the readiness-assimilation relationship, but it remained statistically significant, suggesting that assimilation has practical innovation relevance.

H4 was supported. Organizational learning capability had a positive effect on innovation performance. This finding is central to the study's argument because it shows that innovation benefits depend on the firm's ability to convert AI-supported experience into shared knowledge and improved routines. AI can provide new information, but learning capability determines whether that information becomes organizationally useful.

The model also included a direct path from AI readiness to innovation performance. This path was positive and significant. It was reported as a model-completion path rather than as a separate hypothesis. Its inclusion shows that the mediation mechanism is partial rather than full. In practical terms, AI readiness appears to influence innovation both directly and indirectly through AI assimilation and organizational learning capability.

4.5 Mediation, Moderation, and Robustness Results

Table 6 presents the mediation and moderation results. The robustness checks are reported after the table because they were used as sensitivity analyses rather than as separate hypothesis tests. H5 was supported. The bootstrapped serial indirect effect from AI readiness to innovation performance through AI assimilation and organizational learning capability was positive, and the confidence interval did not include zero. This result supports the central mechanism of the study. AI readiness contributes to innovation performance partly by enabling AI assimilation, while AI assimilation contributes to innovation performance by strengthening organizational learning capability.

Table 6. Mediation and moderation results

Hypothesis	Tested effect	Estimate	95% CI	p	Decision	Interpretation
H5	AI readiness → AI assimilation → Organizational learning capability → Innovation performance	0.047	[0.021, 0.077]	< .05	Supported	AI readiness contributes to innovation performance partly through the sequential mechanism of AI assimilation and organizational learning capability.
H6	AI assimilation × Knowledge-sharing climate → Organizational learning capability	0.045	[-0.067, 0.151]	.419	Not supported	Knowledge-sharing climate does not significantly strengthen the relationship between AI assimilation and organizational learning capability.
H7	AI readiness × External digital support → AI assimilation	0.077	[-0.046, 0.180]	.153	Not supported	External digital support does not significantly strengthen the relationship between AI readiness and AI assimilation.

Source: By author.

Note: H5 was evaluated through the bootstrapped serial indirect effect. The confidence interval does not include zero, indicating support for the serial mediation hypothesis. H6 and H7 were evaluated through interaction terms in the structural model.

H6 was not supported. The interaction between AI assimilation and knowledge-sharing climate did not have a statistically significant effect on organizational learning capability. This result does not mean that knowledge sharing is unimportant. Knowledge-sharing climate had a significant direct relationship with organizational learning capability in the structural model. However, it did not significantly strengthen the relationship between AI assimilation and learning. One possible explanation is that knowledge-sharing practices in Greek SMEs are often informal and uneven, which may limit their ability to consistently amplify AI-enabled learning.

H7 was not supported. The interaction between AI readiness and external digital support did not have a statistically significant effect on AI assimilation. External digital support had a significant direct relationship with AI assimilation, but it did not significantly strengthen the readiness-assimilation relationship. This finding suggests that external support may directly help firms, but it does not automatically translate readiness into assimilation. External support may need to be more specific, more sector-sensitive, and more closely aligned with internal readiness gaps.

The robustness checks were interpreted cautiously. The full-sample sensitivity model produced a positive serial-chain estimate, but this model was not treated as the primary analysis because firms reporting no AI use cannot be assumed to provide conceptually valid responses to AI assimilation items. The formal-AI-user subsample also produced a positive but weaker serial-chain estimate. This result is directionally consistent with the main model, but it should not be overinterpreted, as the subgroup was small and only 4 firms reported AI embedded across core operations. The robustness checks therefore support the direction of the main interpretation, but the AI-exposed sample remains the most theoretically appropriate basis for hypothesis testing.

5. Discussion

The findings provide a practical explanation of how Greek SMEs convert AI readiness into innovation performance. The supported relationships show that AI readiness increases AI assimilation, AI assimilation strengthens organizational learning capability, and organizational learning capability improves innovation performance. This sequence confirms the study's core argument that AI-related innovation in SMEs is not only a technological issue. It is an organizational capability and learning issue.

The qualitative findings deepen this interpretation. Interview evidence showed that Greek SMEs face difficulties with fragmented data, dependence on owner-managers, limited employee AI literacy, and weak routines for sharing lessons from experimentation. These barriers explain why AI readiness must be conceptualized broadly. Firms need more than access to generative AI tools. They need reliable data, leadership commitment, employee training, responsible-use expectations, and learning routines.

The findings also clarify the role of external support. External support had a significant direct effect on AI assimilation, but the moderation hypothesis was not supported. This means that consultants, vendors, chambers, universities, public programs, and digital innovation initiatives may help SMEs understand and use AI, but they do not necessarily strengthen the effect of internal readiness on assimilation. For managers and policymakers, this suggests that external support should move beyond awareness activities and generic training. It should help SMEs diagnose readiness gaps, improve data quality, develop practical use cases, train employees, and build routines for responsible experimentation.

The lack of support for the knowledge-sharing climate also deserves attention. Knowledge-sharing climate directly supported organizational learning capability, but it did not significantly strengthen the link between AI assimilation and learning. This suggests that knowledge sharing may be a general learning condition rather than a specific amplifier of AI-enabled learning. In Greek SMEs, informal knowledge exchange may help firms learn, but more structured mechanisms may be needed to ensure that AI-related lessons are systematically shared and embedded in organizational routines.

6. Conclusions

This study examined how AI readiness is converted into innovation performance in Greek SMEs. The findings show that readiness supports assimilation, that assimilation strengthens organizational learning capability, and that learning capability improves innovation performance. The serial mediation result confirms the central argument of the paper. AI does not generate innovation value simply because firms access or experiment with new tools. It becomes innovation-relevant when firms possess the readiness conditions needed to embed AI into routines and convert AI-supported experience into shared organizational learning.

The main contribution of this study is to clarify the organizational mechanism linking AI readiness to innovation performance in SMEs. The study contributes to management and organization research by treating AI readiness as a multidimensional organizational capability, by distinguishing assimilation from initial adoption, and by showing that organizational learning capability partly explains how AI-enabled activity becomes innovation performance. This contribution shifts attention from whether SMEs use AI to how they organize, learn, and redesign routines around AI use.

The findings also offer practical implications for SME managers and policy actors. Managers should not treat AI adoption as a simple software or tool-purchasing decision. They should first assess whether their firms have reliable data, sufficient digital infrastructure, leadership commitment, employee skills, responsible-use expectations, and routines for learning from experimentation. They should then embed AI into specific business routines, including customer service, marketing, forecasting, process improvement, service design, and internal decision-making. External support programs should also move beyond general awareness and provide targeted assistance with readiness diagnosis, data quality, use-case development, employee training, and responsible experimentation.

The study has limitations that create opportunities for future research. The sample was designed to provide variation in AI exposure and organizational readiness, not to estimate national population prevalence. The cross-sectional survey design limits causal inference, and the use of managerial perceptions may introduce common-method concerns despite the procedural and statistical safeguards used in the study. Future research should examine the model longitudinally to show how readiness, assimilation, learning, and innovation evolve over time. Comparative studies should test whether the model operates differently across European countries with different levels of digital maturity. Sector-specific studies should examine whether tourism, retail, manufacturing, logistics, professional services, and education-based SMEs use distinct learning routines to convert AI into innovation. Future studies should also examine whether generative AI affects the speed of strategic decision-making and innovation performance in SMEs [31] and whether technology, organizational, and environmental conditions jointly explain differences in AI adoption depth across SME contexts [32]. Qualitative case studies could further explain how SMEs develop responsible AI governance and how external digital support becomes embedded in everyday routines.

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Conflicts of Interest

The author confirms that there are no conflicts of interest.

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