Generative AI - Driven Reconstruction of Innovation Models in SMEs: Mechanisms and Pathways from Knowledge Creation to Intelligent Decision-making

Weixiang Gan, Mengfei Xiao*
Graduate School of Business, SEGi University, Petaling Jaya 47810, Malaysia
*Corresponding email: seanphydiyas@gmail.com

Abstract

The rapid advance of generative artificial intelligence (GenAI) is reshaping the innovation logic of small and medium-sized enterprises (SMEs), driving a profound shift from "human-led and technology-assisted" processes toward "human-AI collaboration and algorithmic co-creation". Grounded in the knowledge-based view and dynamic capability theory, this study develops and validates a systematic mechanism of GenAI-driven innovation model reconstruction. It identifies how GenAI facilitates knowledge creation, strengthens firms' innovation capabilities, and ultimately enhances the formation of intelligent decision-making systems. Using a sample of 412 SMEs and Structural Equation Modelling (SEM) for empirical analysis, the results demonstrate that GenAI applications exert a significant positive influence on knowledge creation, which in turn substantially enhances innovation capability. Innovation capability functions as a key mediator between knowledge creation and intelligent decision-making. In addition to its indirect effects through knowledge and innovation mechanisms, GenAI also directly improves managerial strategic judgment through its reasoning, prediction, and solution-evaluation functions. The overall model confirms a robust sequential chain - "GenAI - knowledge creation - innovation capability - intelligent decision-making". It exhibits strong explanatory power and stable path relationships. The study makes theoretical contributions by introducing the concepts of "algorithm-participatory knowledge creation" and "AI-enhanced dynamic capability", thereby expanding research frontiers in digital innovation and organisational intelligence. Practically, it offers a structured pathway for SMEs seeking knowledge-driven innovation transformation and decision-making optimisation in the GenAI era, while also providing insights for policymakers aiming to promote AI-enabled SME development.

Keywords

Generative artificial intelligence, Small and medium-sized enterprises, Knowledge creation, Innovation capability, Intelligent decision-making, Dynamic capability

Introduction

In recent years, generative artificial intelligence (GenAI) - supported by large-scale models, multimodal generation, and advanced semantic reasoning. They have moved beyond the boundaries of traditional "tool-based AI". Meanwhile, these have gradually evolved into a new type of intelligent agent capable of directly participating in knowledge production, creative generation, and complex reasoning. Its powerful capacities in text generation, image synthesis, code development, and cross-domain knowledge integration are driving a profound transformation. In organisational innovation processes, they are shifted from "experience-driven" to "algorithm-driven" and from "human-created knowledge" to "human-AI co-created knowledge". For small and medium-sized enterprises (SMEs) - which typically face limited resources, constrained capabilities, and high uncertainty - GenAI's functions (knowledge amplification, cognitive enhancement, and workflow reconstruction) substantially lower innovation barriers. This enables SMEs to conduct technological development, product design, and strategic planning more efficiently and at significantly reduced costs. However, existing research remains insufficient in explaining how GenAI reshapes internal knowledge-creation mechanisms, strengthens innovation capabilities, and facilitates the development of intelligent decision-making systems within firms. A coherent and integrative theoretical framework is still lacking.

Drawing on the knowledge-based view and Nonaka's SECI model, GenAI has the potential to intervene deeply in all four phases of organisational knowledge creation: socialization, externalization, combination, and internalization. It can extract implicit knowledge patterns from large-scale datasets, transform vague ideas into structured design prototypes, and integrate cross-domain knowledge via interactive learning. This thereby accelerates the processes of organisational absorption and internalization. This evolution reflects a shift from human-centric knowledge creation toward a collaborative human - AI knowledge ecosystem. From the perspective of dynamic capability theory, GenAI enhances firms' abilities in opportunity recognition, resource orchestration, and capability reconfiguration through functions such as intelligent search, scenario simulation, automated design, and rapid prototyping. These capabilities contribute to the formation of an innovative capability structure in which artificial intelligence (AI) becomes a central driving force. Furthermore, by providing advanced prediction, reasoning, and evaluative functions, GenAI supports the development of data-driven, algorithm-supported decision-making systems, reducing managerial cognitive burdens and improving the scientific rigour and robustness of strategic judgment. Consequently, GenAI is fostering a continuous mechanism in SMEs in which enhanced knowledge creation feeds into strengthened innovation capabilities, which in turn support optimized intelligent decision-making.

Building on these theoretical insights, this study aims to construct a GenAI-driven innovation model reconstruction mechanism. This mechanism systematically explains how GenAI intervenes at the knowledge creation starting point, permeates the innovation process, and ultimately drives the intelligent transformation of decision-making systems. Specifically, the research addresses four core questions: How does GenAI reshape the knowledge-creation mechanisms of SMEs? How does AI-generated knowledge contribute to the formation of innovation capabilities? Through what pathways does GenAI influence intelligent decision-making in enterprises? And under what organisational conditions can this innovation model achieve optimal performance?

The theoretical contributions of this study are threefold:

(1) Introducing the concept of "algorithm-participatory knowledge creation", which extends the application boundary of the knowledge-based view (KBV).

(2) Integrating GenAI into the dynamic capability framework via the notion of "AI-enhanced dynamic capability".

(3) Developing an integrated mechanism model that links AI, knowledge, innovation, and decision-making.

In practical terms, this study provides SMEs with a structured pathway to design AI-enabled innovation strategies, optimize innovation processes, and build intelligent decision-making systems. It also provides policy implications for governments seeking to promote the adoption of AI among SMEs.

Literature review

The evolution of GenAI and its core characteristics

GenAI, as a key outcome of advances in deep learning and large-scale pre-training techniques, has rapidly emerged as a focal point in both global technological research and industrial applications since 2022. Its core capabilities span text generation, code generation, image and video synthesis, multimodal reasoning, and deep semantic understanding. These capabilities have enabled AI to shift from traditional "pattern recognition" toward "content production and knowledge generation". A growing body of research emphasizes that the fundamental distinction between GenAI and earlier forms of AI lies in its capacity to reconstruct structured knowledge from raw data and generate novel expressions, thereby granting it the potential to participate directly in innovation activities [1,2].

With the rapid maturation of large language models (LLMs) and multimodal large models such as GPT-4, Gemini, and Claude 3, scholarly attention has increasingly turned to the cognitive enhancement properties of GenAI - including human-like logical reasoning, semantic generalization, cross-lingual transfer, and multimodal integration [3]. These capabilities have elevated GenAI from a mere task-execution tool to a "knowledge agent" capable of co-producing knowledge alongside human actors. In the fields of organisational management and innovation research, GenAI is viewed as a disruptive technological force that can reshape knowledge flows, redesign innovation processes, and transform managerial decision-making mechanisms [4]. Overall, the rise of GenAI signifies a paradigm shift in which algorithms evolve from "decision-support tools" to "co-decision entities", and from "data analytics instruments" to "knowledge-generating participants". Underscoring deep transformations in the conceptual, procedural, and cognitive dimensions of organisational innovation [5].

Mechanisms of GenAI in organisational knowledge creation

Knowledge creation has long been regarded as the central driving force behind corporate innovation. The classic SECI model proposed by Nonaka and Takeuchi posits that knowledge evolves continuously through the processes of socialization, externalization, combination, and internalization. With the rise of GenAI, however, algorithms are increasingly shifting from supportive knowledge-management tools to active participants in the knowledge-creation process [6]. Pichman's research demonstrates that large language models (LLMs), leveraging deep learning and semantic modeling techniques, can discern latent structures inherent in linguistic and experiential datasets, and generate content that is comparable in quality to expert-derived insights [7]. This capability thereby facilitates the algorithmic extraction of tacit knowledge and the production of quasi-experiential content. This capability provides strong support for organizations - especially SMEs lacking access to specialised human capital - to obtain high-quality knowledge generation inputs.

GenAI also demonstrates significant advantages in the externalization stage of knowledge creation. It can transform vague managerial or R&D concepts into structured texts, product prototypes, or executable code. This approach can substantially enhance the efficiency of knowledge articulation and dissemination [8]. Furthermore, GenAI's multimodal reasoning and cross-domain semantic integration capacities enable it to play a pivotal role in knowledge combination and innovation processes. By integrating information resources from markets, technologies, finance, and user experience, GenAI facilitates cross-domain knowledge fusion and opens new innovation avenues [9]. Meanwhile, interactive AI systems support continuous learning and feedback cycles that accelerate organisational knowledge absorption and internalization, forming a "non-linear acceleration effect" that expedites knowledge transformation and renewal [10]. Collectively, these developments indicate that GenAI is driving a shift in organisational knowledge-creation paradigms from traditional "human-led, technology-assisted" modes to "human-AI collaborative, algorithm-co-creative" systems. This transformation not only reshapes the mechanisms of knowledge generation but also equips organizations with enhanced cognitive capacity for sustained innovation [11].

The impact of GenAI on SME innovation capability and decision-making

As GenAI becomes more deeply embedded in organisational processes, scholars have increasingly examined its role in reshaping innovative workflows, enhancing innovation capability, and transforming strategic decision-making. From the perspective of the dynamic capabilities theory proposed by David Teece, the core of innovation lies in three interconnected dimensions: sensing opportunities, seizing resources, and transforming capabilities [12]. GenAI is rapidly emerging as a key driver reinforcing each of these processes. In the opportunity-sensing stage, GenAI's ability to analyse market data, consumer behaviour, and technological trends in real time reduces information asymmetries and enables SMEs to identify potential opportunities and innovation directions more effectively [13]. At the same time, AI demonstrates pronounced efficiency advantages in resource orchestration and product development. It can automatically generate requirement documents, code segments, and design prototypes, thereby enabling swift transitions from ideation to implementation [14]. This automation-driven innovation workflow shortens iteration cycles and enhances agility, resulting in more data-driven and responsive innovation processes [15].

Moreover, GenAI is pushing firms toward a shift from linear, stage-based innovation models to cyclic, real-time adaptive "intelligent innovation systems". Interactive AI tools promote dynamic learning through continuous feedback, allowing self-correction and knowledge regeneration at every stage of the innovation cycle [16]. In strategic decision-making, GenAI's scenario simulation and system-level reasoning capabilities significantly enhance the scientific rigor and forward-looking nature of managerial decisions. GenAI can generate multiple strategic alternatives under various scenarios, aiding managers in assessing risks, forecasting consequences, and making structured decisions in uncertain environments [17]. These capabilities enable firms - particularly resource-constrained SMEs - to maintain innovative agility and strategic adaptability even under volatile market conditions. Overall, GenAI is facilitating a transition in SMEs from “capability-deficient innovation models” to “AI-enhanced innovation systems”, providing crucial support for developing sustained competitive advantage and dynamic adaptability [18].

Overview of existing research and identification of research gaps

Although the proliferation of GenAI has prompted extensive scholarly discussion on its organisational applications - ranging from content generation and managerial support to its influence on innovation and strategic decision-making - significant theoretical gaps remain.

First, despite increasing recognition of GenAI’s human-like reasoning and knowledge generation capabilities, much of the literature continues to conceptualize AI primarily as a supportive instrument rather than as an active participant in knowledge creation. There is still limited systematic inquiry into how GenAI contributes to the transformation between tacit and explicit knowledge, how it modifies the knowledge cycle within the SECI model, and how it supports knowledge absorption and expansion in SMEs.

Second, research on how GenAI fundamentally reshapes innovation capability remains underdeveloped. Existing studies often focus on efficiency improvements rather than analysing how AI alters the deeper mechanisms of opportunity sensing, knowledge integration, and capability reconfiguration - issues particularly vital for resource-constrained SMEs. Third, while the value of GenAI in strategic decision-making is increasingly noted, academic discussions largely emphasize predictive analytics or data-driven insights, overlooking how GenAI reshapes managerial cognition, organisational judgement processes, and strategic logic. Furthermore, research has yet to explain how AI enhances decision quality in environments characterized by high uncertainty.

Finally, existing literature lacks an integrated framework that connects “knowledge creation - innovation capability - intelligent decision-making”. Current studies remain fragmented, offering limited understanding of how AI-generated knowledge enters innovation processes, how innovation capability subsequently shapes decision systems, and whether GenAI reshapes the internal interactions between knowledge and decision-making. In sum, the field still lacks a comprehensive depiction of the full mechanism through which GenAI influences organisational innovation. Addressing these voids forms the central theoretical contribution of the present study.

Theoretical model and hypotheses

Theoretical model

The theoretical model developed in this study centres on the role of GenAI in reshaping organisational innovation models, illustrating a sequential mechanism that runs from knowledge creation, to the formation of innovation capability, and ultimately to the optimisation of intelligent decision-making. The model integrates the knowledge-based view, dynamic capability theory, and intelligent decision-making theory to capture the systemic influence of GenAI on firms’ internal capability structures.

At the knowledge-creation stage, GenAI enhances the efficiency of knowledge acquisition, absorption, and reconstruction through its capabilities in content generation, cross-domain knowledge integration, semantic reasoning, and automated expression. These functions enable firms to obtain richer, more structured, and more actionable knowledge foundations within a shorter time frame. During the innovation-capability formation stage, GenAI becomes embedded in R&D, prototyping, idea generation, and iterative testing, helping firms to identify opportunities more sensitively, integrate resources more effectively, and restructure processes to develop new configurations of innovation capability.

Finally, at the decision-making stage, continuous interaction with AI throughout the innovation process enables enhanced innovation capability to translate into more robust strategic analysis, risk assessment, and option evaluation, thereby rendering the decision-making system more intelligent, data-driven, and forward-looking. Together, these three mechanisms form an integrated causal chain in which GenAI strengthens knowledge creation, which in turn enhances innovation capability and further leads to improved intelligent decision-making. As shown in Figure 1, through this positive and reinforcing cycle, the model reflects the ongoing evolution of firms' innovation systems in the GenAI era.

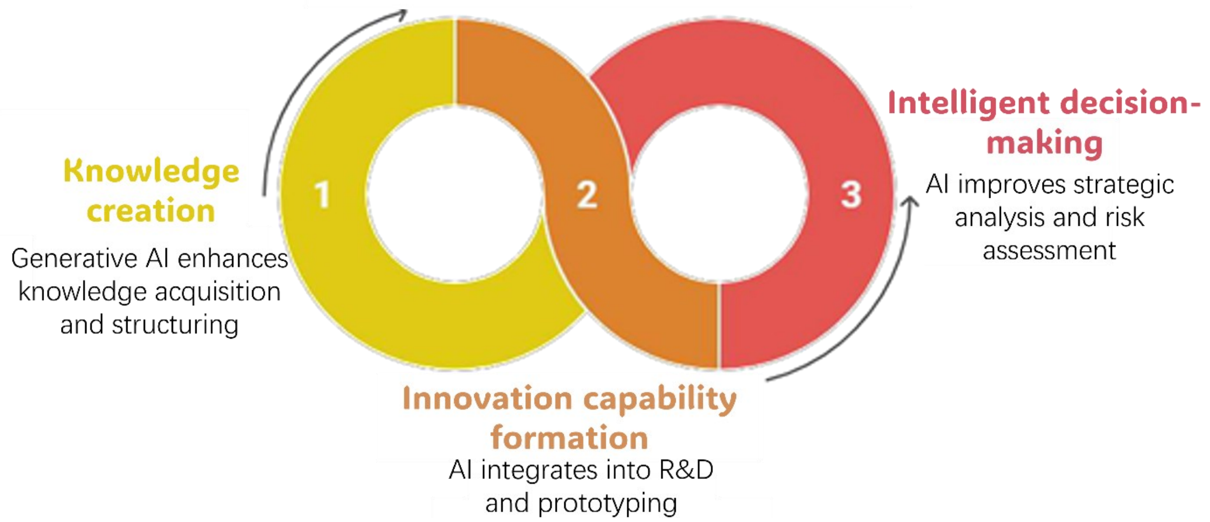

Figure 1. GenAI innovation cycle.

Development of hypotheses

H_1: The application of GenAI will significantly enhance firms' knowledge-creation capability.

GenAI substantially expands a firm's knowledge base through its capabilities in text generation, knowledge extraction, semantic integration, and cross-domain information fusion. According to the knowledge-based view (KBV), a firm's competitive advantage rests on its ability to create and utilise knowledge [19]. GenAI has been shown to increase the efficiency of knowledge articulation, strengthen cross-domain information integration, and accelerate organisational learning and absorptive capacity [20]. Its generative and reasoning functions enrich knowledge content and structurally strengthen the knowledge-creation process. Hence, it is theoretically justified to expect that GenAI directly enhances firms' knowledge-creation capability.

H_2: AI-enhanced knowledge creation will significantly strengthen firms' innovation capability.

Building knowledge creation, AI-enhanced abilities in knowledge acquisition, absorption, and integration provide the essential informational and cognitive foundations for innovation. Innovation depends on a firm's ability to recognize, assimilate, and apply new knowledge [21]. GenAI facilitates knowledge flows, improves absorption efficiency, and increases the availability of cross-domain information, enabling firms to demonstrate stronger innovation potential in idea generation, problem solving, and solution design. Existing research indicates that AI significantly supports both exploratory and exploitative innovation, improving R&D efficiency and innovation outcomes [22].

H_3: The application of GenAI will directly improve firms' innovation capability.

Beyond this indirect influence, GenAI also contributes directly to innovation capability through its technological and process-based affordances. It can automatically generate requirement documents, code, user interface prototypes, and market insights. Moreover, its capabilities in design simulation and rapid iteration have been shown to shorten product development cycles and improve innovation quality [23]. Thus, GenAI enhances innovation not only through knowledge mechanisms but also through its direct functions and its ability to reshape organisational processes.

H_4: Innovation capability will significantly enhance firms' intelligent decision-making.

Innovation capability, as a central manifestation of dynamic capability, enhances a firm's ability to sense opportunities, integrate resources, and reconfigure capabilities [24]. The ability thereby exerts a direct influence on decision quality in complex environments. Firms with stronger innovation capabilities are better positioned to interpret market changes, anticipate risks, evaluate strategic alternatives, and make decisions that are more timely, rigorous, and accurate [25]. Therefore, Innovation capability not only represents technological strength but also constitutes an essential cognitive foundation for strategic judgement. It is thus expected to significantly enhance intelligent decision-making.

H_5: Innovation capability mediates the relationship between AI-enhanced knowledge creation and intelligent decision-making.

Following the classical organisational learning and strategic management pathway - "knowledge - innovation capability - decision-making capability", the influence of knowledge creation on decision-making is typically indirect, operating through innovation capability as a key organisational mechanism. Scholars note that the impact of AI-generated knowledge on decision systems depends on whether firms can translate such knowledge into actionable innovation outputs and foundational capabilities [26]. Thus, AI-enhanced knowledge creation must operate through strengthened innovation capability to ultimately improve decision quality, forming a chained mediation effect.

H_6: The application of GenAI will directly enhance firms' intelligent decision-making.

Although innovation capability plays a central mediating role between knowledge and decision-making, a substantial body of research indicates that GenAI can directly enhance firms' strategic decision quality through its reasoning, predictive modelling, scenario simulation, and alternative-comparison functions [27]. GenAI's cognitive-augmentation effects reduce managerial cognitive burden, improve risk recognition, and enhance resource-allocation efficiency. Thus, its influence on decision-making is not entirely dependent on innovation capability but can arise independently.

Research methodology

This study aims to systematically examine how GenAI enhances knowledge-creation mechanisms in small and medium-sized enterprises (SMEs). It can help to strengthen their innovation capability and further advance the intelligent transformation of their decision-making systems. The methodological design follows a positivist paradigm and adopts Structural Equation Modelling (SEM) as the principal analytical tool to enable rigorous testing of the multi-level mechanisms proposed in the theoretical model. This chapter presents the research design, variable measurement, questionnaire development, data collection procedures, sampling strategy, and statistical methods.

Research design

A quantitative research design was employed, using a structured questionnaire to collect data from SME managers regarding their application of GenAI, knowledge-creation processes, innovation capability, and level of intelligent decision-making. This methodological choice rests on three considerations. First, the theoretical model involves multiple causal pathways requiring simultaneous estimation of direct, indirect, and mediating effects. Therefore, SEM provides the most appropriate statistical framework. Second, the mechanisms associated with GenAI involve abstract psychological constructs and organisational behaviour variables, which require standardised measurement scales for empirical validation. Third, the target sample size is manageable, and a cross-sectional survey allows for efficient data collection from firms across diverse industries. It makes the approach both feasible and representative.

Given the clear theoretical relationships among variables and the presence of hypothesized causal pathways, this study adopts covariance-based SEM (AMOS) to perform confirmatory factor analysis (CFA) and estimate the structural paths. This choice ensures strong model fit, measurement reliability, and robust causal inference.

Measurement of variables

The measurement framework consists of one exogenous variable and three core mediating constructs, all assessed using a unified five-point Likert scale ranging from "strongly disagree" to "strongly agree". To ensure reliability and contextual appropriateness, all measurement items were adapted from validated international scales and refined based on the organisational application context of GenAI.

The application of GenAI is measured by assessing the extent to which firms utilise GenAI tools for knowledge generation, text processing, semantic reasoning, creative design, and predictive analysis. The scaling development draws on the research of Florea [28]. Example items include: "The firm frequently uses GenAI for content generation and idea development" and "AI plays an important role in information analysis and internal communication processes".

AI-enhanced knowledge creation reflects the extent to which GenAI strengthens a firm's capability to acquire, absorb, combine, and articulate knowledge. The scale design is based on the SECI model of Nonaka and Takeuchi and research on AI-enabled learning and knowledge transformation [29]. Example items include:

"GenAI helps the firm access more diverse sources of knowledge" and "AI accelerates the absorption and application of external knowledge".

Innovation capability measures the firm's ability to identify opportunities, develop technologies, design new products, and optimise processes. Scale development draws from Teece's dynamic capability framework and empirical findings on AI-driven innovation performance [30,31]. Example items include: "The firm can use digital tools to quickly identify market and technological opportunities" and "AI significantly improves new product development efficiency".

Intelligent decision-making assesses the breadth and effectiveness of AI-supported decision processes in strategic planning, resource allocation, and risk management. Item development is primarily and closely informed by Brynjolfsson, Kalogiannidis and Stanojević, with emphasis on AI's role in scenario analysis, solution evaluation, and risk prediction [32,33].

Vujović proposed in the study that, to account for sample heterogeneity, firm size, firm age, industry sector, managers' digital competencies, and firms' prior experience in AI adoption were incorporated into the analysis as control variables. Empirical studies have demonstrated that these factors exert a tangible impact on firms' knowledge application behaviors, innovation initiatives, and decision-making mechanisms.

Questionnaire development and pilot testing

The questionnaire development process follows rigorous scale-construction standards to ensure validity and reliability at both structural and statistical levels. First, the initial pool of items was drafted based on the theoretical model and established international scales to ensure comprehensive coverage of each construct. Contextual modifications were introduced to reflect the organisational use of GenAI.

The initial version was subsequently reviewed by three experts specialising in management and AI, who evaluated the clarity, conceptual alignment, and structural coherence of each item. Their feedback was incorporated through targeted revisions. A pilot test involving 30-50 SMEs was then conducted. Using SPSS or AMOS, reliability and validity were assessed, including whether Cronbach's alpha exceeded 0.70, item-total correlations surpassed 0.50, KMO values were higher than 0.70, Bartlett's test was significant, and all factor loadings reached at least 0.60. Items that failed to meet these criteria were refined or removed to ensure a high-quality final instrument.

Data collection

Data collection focuses on SMEs that have already been adopted or intended to adopt GenAI tools. Respondents included founders, senior managers, department heads, and individuals responsible for technology or innovation, ensuring that participants possessed sufficient knowledge of their firm's digitalization and innovation activities.

Sampling was conducted through national and regional SME service centres, industry associations in the technology services and manufacturing sectors, science parks, incubators, and online survey platforms with managerial identity verification. To meet SEM sample-size requirements - typically 10-15 times the number of measurement items - this study targets 350-450 valid responses to ensure adequate model fit and statistical robustness.

Several quality control measures were implemented: Reverse-coded items and attention-check questions were included to detect inattentive responses; questionnaires with abnormally short completion times or signs of automated answering were removed; IP restrictions and duplication checks were applied to prevent repeated submissions. These procedures ensure a high-quality and reliable final dataset.

Data analysis techniques

Data analysis follows a two-stage SEM approach to ensure measurement quality and robust structural estimation. In the first stage, confirmatory factor analysis (CFA) evaluates reliability and validity. Specifically, standardised factor loadings should exceed 0.60, composite reliability (CR) should be above 0.70, and average variance extracted (AVE) should exceed 0.50. Discriminant validity is examined using both the Fornell-Larcker criterion and the HTMT ratio (threshold < 0.85). In the second stage, the structural model is assessed by estimating the path coefficients (β) corresponding to hypotheses H_1-H_6 and their statistical significance. Model fit is evaluated using indices such as CFI, TLI, RMSEA, and SRMR. Bootstrapping with 5,000 resamples is used to assess the significance of mediating effects. Model explanatory and predictive power are evaluated through R^2 and Q^2 values. Additional analyses may include the effects of control variables or potential moderating factors.

To ensure robustness, alternative model comparisons (e.g., re-estimating the model after removing selected paths), subgroup analyses (e.g., large vs small firms, high vs low AI-experience firms), and sensitivity tests involving adjustments to measurement items or structure will be conducted. This ensures consistency and reliability in the study's conclusions.

Empirical analysis and results

Descriptive statistics of the sample

As shown in Table 1, a total of 412 valid questionnaires were collected for this study, representing SMEs from the manufacturing sector, digital services, technological R&D services, and other related industries. Among the sampled firms, 41.3% had fewer than 50 employees, 38.8% had between 50 and 150 employees, and the remaining 19.9% had more than 150 employees. In terms of industry distribution, 33.2% of the firms operated in manufacturing, 27.1% in digital technology and information services, 21.4% in technology services and R&D-oriented industries, and 18.3% in other sectors. Regarding respondents' positions within their organisations, 46.6% were founders or senior executives, 37.8% were department managers or mid-level administrators, and 15.6% were responsible for technology or innovation-related functions. Overall, the diversity of the sample in terms of firm size, industry type, and managerial roles ensures substantial representativeness and provides a robust foundation for the Structural Equation Modelling conducted in this study.

Table 1. Descriptive statistics of the sample.

Category	Subgroup	Frequency (%)
Enterprise size	Fewer than 50 employees	41.3%
	50-150 employees	38.8%
	More than 150 employees	19.9%
Industry sector	Manufacturing	33.2%
	Digital technology & information services	27.1%
	Science & technology services / R&D	21.4%
	Other industries	18.3%
Position of respondents	Founder / Senior executive	46.6%
	Department manager / Middle management	37.8%
	Technology / Innovation manager	15.6%
Total valid responses	412	100.0%

Reliability and validity analysis

The reliability analysis shows that all four core variables in this study - GenAI application, AI-enhanced knowledge creation, innovation capability, and intelligent decision-making - exhibit high levels of internal consistency. Data presented in Table 2 indicates that the Cronbach's α values for all constructs exceed 0.870, while the composite reliability (CR) values are all above 0.900. These results indicate that the measurement items demonstrate strong stability in capturing their respective latent constructs, with satisfactory inter-item correlations and coherence. Such high reliability provides a solid foundation for subsequent validity testing and structural model evaluation.

Further validity assessments confirm that the measurement scales possess strong convergent and discriminant validity. As shown in Table 3, in terms of convergent validity, all standardised factor loadings are statistically significant and fall within the range of 0.67 to 0.89. The average variance extracted (AVE) values for all constructions range from 0.65 to 0.71, exceeding the recommended threshold of 0.50. These findings confirm that the items effectively represent the corresponding latent constructions.

Regarding discriminant validity, as shown in Table 4 and Table 5, both the Fornell-Larcker criterion and the HTMT ratio results demonstrate clear distinctions among constructs, indicating that the scales successfully differentiate between the latent variables and avoid conceptual overlap. Overall, the measurement model exhibits robust validity and is suitable for further structural analysis.

Table 2. Reliability analysis.

Construct	Cronbach’s α	Composite reliability (CR)
GenAI utilisation	0.881	0.922
AI-augmented knowledge creation	0.874	0.915
Innovation capability	0.892	0.934
Intelligent decision-making	0.879	0.918

Table 3. Convergent validity.

Construct	Factor loadings	AVE
GenAI utilisation	0.72, 0.81, 0.85, 0.88	0.68
AI-augmented knowledge creation	0.70, 0.77, 0.83, 0.87	0.66
Innovation capability	0.75, 0.82, 0.86, 0.89	0.71
Intelligent decision-making	0.69, 0.80, 0.84, 0.88	0.67

Table 4. Discriminant validity.

Construct	GU	IKC	IC	IDM
GenAI utilisation (GU)	0.825	/	/	/
AI-augmented knowledge creation (IKC)	0.612	0.812	/	/
Innovation capability (IC)	0.588	0.641	0.843	/
Intelligent decision-making (IDM)	0.553	0.603	0.678	0.819

Table 5. HTMT ratio.

Construct Pair	HTMT
GU - IKC	0.74
GU - IC	0.71
GU - IDM	0.69
IKC - IC	0.76
IKC - IDM	0.72
IC - IDM	0.79

Measurement model fit

As shown in Table 6, the confirmatory factor analysis (CFA) indicates that the measurement model demonstrates a satisfactory overall fit. The chi-square divided by degrees of freedom (X^2/df) equals 2.410, which falls within the recommended range widely accepted in literature. The Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) are 0.953 and 0.945 respectively, both exceeding the threshold of 0.900, suggesting strong model fit. The Root Mean Square Error of Approximation (RMSEA) is 0.058, and the Standardised Root Mean Square Residual (SRMR) is 0.041, both well below the conventional benchmark of 0.080. Taken together, these results confirm that the measurement model is structurally sound and exhibits good fit, thereby providing a robust foundation for subsequent structural model analysis.

Table 6. Measurement model fit indices.

Fit index	Value	Threshold	Assessment
X^2/df	2.410	<3.00	Good fit
CFI	0.953	>0.90	Good fit
TLI	0.945	>0.90	Good fit
RMSEA	0.058	<0.08	Good fit
SRMR	0.041	<0.08	Good fit

Structural model analysis

In the structural model analysis, as shown in Table 7, all six hypotheses proposed in this study were rigorously tested, and the results indicate that all hypothesised paths are highly significant, providing strong empirical support for the overall model. First, the application of GenAI exerts a significant positive effect on knowledge creation (β=0.56, $p<0.001$), confirming H_1 and demonstrating that the use of AI tools effectively enhances firms’ capabilities in knowledge generation and absorption. Second, knowledge creation significantly promotes innovation capability (β=0.47, $p<0.001$), supporting H_2 and indicating that a richer and more structured knowledge base contributes meaningfully to the development of innovation capability.

Furthermore, the application of GenAI not only influences innovation capability indirectly through knowledge creation but also directly improves firms’ innovation performance (β=0.31, $p<0.001$), supporting H_3 and highlighting AI’s direct value in enhancing R&D efficiency, idea generation, and process optimisation. Innovation capability is found to have the strongest direct effect on intelligent decision-making (β=0.52, $p<0.001$), supporting H_4, suggesting that firms with stronger innovation capability are more capable of making rigorous and well-informed strategic decisions in complex environments.

Table 7. Structural model path coefficients.

Hypothesis	Path	Standardised coefficient	p-value
H_1	GenAI utilisation - knowledge creation	0.56	<0.001
H_2	Knowledge creation - Innovation capability	0.47	<0.001
H_3	GenAI utilisation - innovation capability	0.31	<0.001
H_4	Innovation capability - intelligent decision-making	0.52	<0.001
H_5	Knowledge creation - innovation capability - intelligent decision-making (indirect)	0.24	<0.001
H_6	GenAI utilisation - intelligent decision-making	0.28	<0.001

As shown in Table 8, in terms of mediation effects, knowledge creation significantly affects intelligent decision-making through innovation capability, with a two-stage mediation effect of 0.24 ($p<0.001$), indicating that innovation capability serves as a critical mechanism through which knowledge is transformed into decision-making advantages. Additionally, the indirect effect of GenAI - knowledge creation - innovation capability is 0.26 ($p<0.001$), further demonstrating that the influence of AI on innovation is both direct and contingent on the enhancement of the knowledge system. The chained mediation effect shows that GenAI shapes intelligent decision-making through the sequential pathway of "knowledge creation - innovation capability" (indirect effect = 0.14, $p<0.001$), thereby confirming H_5.

Finally, the application of GenAI also has a significant direct impact on intelligent decision-making ($\beta=0.28$, $p<0.001$), supporting H_6 and indicating that AI's predictive, inferential, and decision-support functions can independently enhance managerial decision quality. Taken together, all hypotheses receive strong statistical support, and the directions of the effects align fully with theoretical expectations, demonstrating a well-functioning structural mechanism through the chain "GenAI - knowledge creation - innovation capability - intelligent decision-making".

Table 8. Mediation analysis (bootstrapping results, 5000 samples).

Mediation path	Indirect effect	Direct effect	Total effect	Bootstrapped 95% CI	p-value	Conclusion
Knowledge creation - innovation capability - intelligent decision-making	0.24	0.52	0.76	[0.14,0.33]	<0.001	Supported
GenAI utilisation - knowledge creation - innovation capability	0.26	0.31	0.57	[0.17,0.36]	<0.001	Supported
GenAI utilisation - knowledge creation - innovation capability - intelligent decision-making (chain mediation)	0.14	0.28	0.42	[0.07,0.22]	<0.001	Supported

Analysis of model explanatory power

The analysis of explanatory power indicates as Table 9 that all three endogenous variables in the model exhibit satisfactory levels of explanation. The application of

GenAI accounts for a moderate proportion of the variance in knowledge creation (R^2=0.32). Knowledge creation, together with GenAI application, explains 58% of the variance in innovation capability (R^2=0.58), representing a moderately high level of explanatory power. Furthermore, intelligent decision-making, predicted jointly by GenAI application, knowledge creation, and innovation capability, demonstrates a high level of explanatory power with an R^2 value of 0.63.

Overall, the model shows strong explanatory capacity across all key constructs, indicating that the theoretical framework effectively captures how GenAI influences organisational decision-making systems through knowledge and innovation mechanisms.

Table 9. Model explanatory power (R^2 values).

Endogenous construct	R^2 value	Interpretation
Knowledge creation	0.32	Moderate explanatory power
Innovation capability	0.58	Moderate-to-high explanatory power
Intelligent decision-making	0.63	High explanatory power

Conclusion

This study investigates the mechanisms through which GenAI shapes the innovation systems of small and medium-sized enterprises (SMEs), and develops as well as empirically validates an integrated model linking GenAI - knowledge creation - innovation capability - intelligent decision-making. Using Structural Equation Modelling based on 412 valid survey responses, the study not only confirms the theoretical relationships among the core constructs but also reveals how GenAI generates value throughout the entire organisational chain - from knowledge generation to decision optimisation. This chapter summarises the findings in terms of the main empirical results, theoretical contributions, and practical implications.

Key findings

The findings show that GenAI first significantly enhances firms' knowledge-creation capability. Its powerful generative, reasoning, and cross-domain integration functions enable enterprises to acquire, interpret, and organise external knowledge more rapidly than before, while expressing ideas in a clearer and more structured manner. This leads to a more solid and enriched knowledge base. Second, enhanced knowledge creation further promotes the development of innovation capability. The results indicate that firms benefit from stronger knowledge foundations when identifying opportunities, solving problems, advancing technological improvements, and optimising processes. At the same time, GenAI directly accelerates innovation activities through its contribution to R&D design, prototype generation, and process optimisation, making innovation faster and more efficient.

Finally, the study confirms that innovation capability is a key determinant of high-quality strategic decision-making. The influence of GenAI on decision-making occurs primarily through its effect on innovation capability: Firms that learn faster and innovate more effectively are also those that can make more accurate assessments, predictions, and strategic choices in complex environments. Additionally, GenAI itself directly improves decision quality by enabling scenario simulation, solution comparison, and risk analysis, thus providing managers with more reliable decision-support information. Overall, the study clearly demonstrates a cascading mechanism within organisations: GenAI transforms the knowledge system, which then strengthens the innovation system, ultimately shaping the decision-making system. This forms a coherent and complete chain of influence.

Theoretical contributions

This study makes three key theoretical contributions. First, it reconceptualises the role of GenAI in knowledge management. Rather than treating AI as a mere technological tool, the study positions it as an active "knowledge agent" capable of participating in knowledge creation. The results show that GenAI not only processes information but also facilitates the transformation between tacit and explicit knowledge, integrates cross-domain knowledge, and enhances organisational learning efficiency, thereby extending the boundaries of the knowledge-based view and knowledge-creation theory.

Second, the study enriches dynamic capability theory by demonstrating that GenAI contributes to the three core dimensions of dynamic capability - opportunity sensing, resource orchestration, and capability reconfiguration. This provides empirical evidence for the emergence of digital dynamic capabilities, indicating that digital technologies are now deeply embedded in the organisational capability-formation process.

Third, the study develops a holistic theoretical model linking knowledge creation - innovation capability - intelligent decision-making, integrating concepts and mechanisms that have traditionally been examined separately within knowledge management, innovation management, and decision-making research. The model illuminates the continuous chain through which GenAI drives organisational capability evolution. This integrated framework fills existing theoretical gaps and provides a more systematic and scalable foundation for future research.

Practical implications

The findings highlight the practical relevance of GenAI for SMEs undergoing digital and intelligent transformation. First, firms should view GenAI as a “knowledge enhancement engine”, deploying it in knowledge acquisition, semantic analysis, experiential simulation, and content generation to compensate for inherent limitations in expertise and knowledge resources. This strengthens organisational learning and cognitive foundations for innovation.

Second, since GenAI has been shown to reshape innovation processes, firms should integrate AI deeply into R&D activities, prototype development, user needs analysis, and process optimisation. By supporting rapid experimentation and accelerated iteration, GenAI enables low-cost and high-efficiency innovation, allowing SMEs to maintain agility and resilience in highly competitive markets.

Finally, at the decision-making level, managers should fully utilise GenAI for scenario analysis, trend forecasting, risk assessment, and solution evaluation, combining AI’s computational advantages with managerial intuition to develop a hybrid human-AI decision model. The study further reveals that innovation capability is a crucial bridge through which AI improves decision quality. Therefore, when adopting AI tools, firms should simultaneously strengthen their innovation systems to ensure that GenAI can truly and comprehensively enhance strategic decision-making.

Research limitations and recommendations for future research

Although this study develops an integrated theoretical model and empirically validates the systematic influence of GenAI on knowledge creation, innovation capability, and intelligent decision-making, several method-ological and design-related limitations remain. First, the study relies on cross-sectional data, which allows examination of structural relationships but cannot capture the dynamic and evolving nature of GenAI’s impact within organisations. The influence of GenAI is often staged and cumulative, and cross-sectional designs are unable to reveal how organisational capabilities are reconfigured over time. Future studies may therefore employ longitudinal designs, panel data tracking, or event-based analytical approaches to more comprehensively uncover the long-term organisational transformations triggered by AI adoption.

Second, the study is based on self-reported data from managers, which may be affected by subjective judgement, social desirability bias, or cognitive misperceptions, potentially reducing the objectivity and precision of the measurements. Indicators such as the extent of GenAI usage, improvements in knowledge creation, and innovation performance may vary depending on respondents’ individual interpretations. Future research could incorporate objective data - such as internal operational metrics, AI usage logs, or innovation output records - or adopt multi-source data collection, drawing simultaneously from managers, R&D personnel, and frontline employees, thereby enhancing reliability and validity.

A further limitation concerns the study’s focus on SMEs. Although this target group holds strong practical relevance, the findings may not be fully generalisable to large enterprises, multinational corporations, or highly specialised technology-intensive organisations. Future research could conduct comparative studies across different firm sizes, industries, and organisational structures to determine whether the influence mechanisms of GenAI vary under different institutional and organisational contexts.

Finally, the present study focuses primarily on the positive contributions of GenAI, while paying insufficient attention to potential risks - such as algorithmic bias, data privacy concerns, knowledge dependency, or disruptions to employee skill structures - which may affect firms’ long-term sustainable development. Future research could incorporate these risks into a more balanced theoretical framework, examining the organisational challenges and managerial tensions that may accompany AI-enabled transformation. Moreover, as GenAI technologies continue to evolve - particularly with the emergence of multimodal AI and autonomous AI agents - firms may experience deeper shifts in knowledge systems, collaboration patterns, and organisational structures. Future studies may explore how these emerging technological forms reshape organisational behaviour and innovation processes, thereby further extending the theoretical boundaries established in this research.

Funding

This work was not supported by any funds.

Acknowledgements

The authors would like to show sincere thanks to those techniques who have contributed to this research.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Radanliev, P. (2025) Artificial Intelligence: Reflecting on the past and looking towards the next paradigm shift. *Journal of Experimental & Theoretical Artificial Intelligence*, 37(7), 1045-1062.

[2] Ronge, R., Maier, M., Rathgeber, B. (2025) Towards a definition of Generative Artificial Intelligence. *Philosophy & Technology*, 38(1), 31.

[3] Liu, H., Zhang, X., Zhou, J., Shou, Y., Yin, Y., Chai, C. (2025) Cognitive styles and design performances in conceptual design collaboration with GenAI. *International Journal of Technology and Design Education*, 35(3), 1169-1202.

[4] Zhang, R., Xiong, K., Du, H., Niyato, D., Kang, J., Shen, X., Poor, H. V. (2024) Generative AI-enabled vehicular networks: fundamentals, framework, and case study. *IEEE Network*, 38(4), 259-267.

[5] AlDahoul, N., Hong, J., Varvello, M., Zaki, Y. (2025) Towards a World Wide Web powered by generative AI. *Scientific reports*, 15(1), 7251.

[6] Alavi, M., Leidner, D.,Mousavi, R. (2024) Knowledge management perspective of Generative Artificial Intelligence (GenAI). *Alavi, Maryam*, 1-12.

[7] Pichman, B. (2024) Knowledge powered by artificial intelligence. *Information Services and Use*, 44(4), 282-284.

[8] Ruiz-Rojas, L. I., Acosta-Vargas, P., De-Moreta-Llovet, J., Gonzalez-Rodriguez, M. (2023) Empowering education with generative artificial intelligence tools: approach with an instructional design matrix. *Sustainability*, 15(15), 11524.

[9] Bratianu, C., Ioan, A. (2025) Challenges of Artificial Intelligence for knowledge management systems: a bibliometric analysis perspective. *Oradea Journal of Business and Economics*, 10(1), 108-120.

[10] Marshall, A., Bieck, C., Dencik, J., Goehring, B. C., Warrick, R. (2024) How generative AI will drive enterprise innovation. *Strategy & Leadership*, 52(1), 23-28.

[11] Ishaq, R., Gorsi, H., Butt, S., Umair, T., Tajammal, R. (2025) Beyond Automation: Unleashing Creativity and Enhancing Decision-Making with Generative AI. *Academia International Journal for Social Sciences*, 4(1), 911-925.

[12] Teece, D. J. (2018) Dynamic capabilities as (workable) management systems theory. *Journal of Management & Organization*, 24(3), 359-368.

[13] Zipf, S., Wu, C., Petricini, T. (2025) Using the information inequity framework to study GenAI equity: analysis of educational perspectives. *Information Research an International Electronic Journal*, 30, 533-547.

[14] Elahi, M., Afolaranmi, S. O., Martinez Lastra, J. L., Perez Garcia, J. A. (2023) A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. *Discover Artificial Intelligence*, 3(1), 43.

[15] Trabucchi, D., Buganza, T. (2019) Data-driven innovation: Switching the perspective on Big Data. *European Journal of Innovation Management*, 22(1), 23-40.

[16] Essien, A. (2023) AI-driven innovation: Leveraging big data analytics for innovation. *Innovation Analytics: Tools for Competitive Advantage*, 119-137.

[17] Doshi, A. R., Bell, J. J., Mirzayev, E., Vanneste, B. S. (2025) Generative Artificial Intelligence and evaluating strategic decisions. *Strategic*

Management Journal, 46(3), 583-610.

[18] Vujović, D. (2025) Generative AI: a new general-purpose technology for growth and research. *Ekonomika Preduzeća*, 73(1-2), 97-114.

[19] Novianti, K. R. (2019) Achieving competitive advantage through knowledge management practices: knowledge-based view (KBV) strategy on Indonesia electricity sector. *Asia Pacific Management and Business Application (APMBA)*, 7(3), 163-176.

[20] Al Naqbi, H., Bahroun, Z., Ahmed, V. (2024) Enhancing work productivity through Generative Artificial Intelligence: a comprehensive literature review. *Sustainability*, 16(3), 1166.

[21] Ko, W. W., Liu, G. (2019) How information technology assimilation promotes exploratory and exploitative innovation in the small-and medium-sized firm context: the role of contextual ambidexterity and knowledge base. *Journal of Product Innovation Management*, 36(4), 442-466.

[22] Liu, J., Chang, H., Forrest, J. Y. L., Yang, B. (2020) Influence of artificial intelligence on technological innovation: evidence from the panel data of china's manufacturing sectors. *Technological Forecasting and Social Change*, 158, 120142.

[23] Da Silva, R. H., Kaminski, P. C., Armellini, F. (2020) Improving new product development innovation effectiveness by using problem solving tools during the conceptual development phase: Integrating design thinking and TRIZ. *Creativity and Innovation Management*, 29(4), 685-700.

[24] Hussaina, S., Rehmanb, A., Khokharc, M. N., Ejazd, M., Munire, M. (2021) Impact of big data analytics on firm performance with mediating role of decision-making performance and innovation capability. *International Journal of Innovation, Creativity and Change*, 15(5), 1153-1172.

[25] Psomas, E., Kafetzopoulos, D., Gotzamani, K. (2018) Determinants of company innovation and market performance. *The TQM Journal*, 30(1), 54-73.

[26] Bag, S., Gupta, S., Kumar, A., Sivarajah, U. (2021) An integrated Artificial Intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance. *Industrial Marketing Management*, 92, 178-189.

[27] Feser, D. (2023) Innovation intermediaries revised: a systematic literature review on innovation intermediaries' role for knowledge sharing. *Review of Managerial Science*, 17(5), 1827-1862.

[28] Florea, N. V., Croitoru, G. (2025). The impact of Artificial Intelligence on communication dynamics and performance in organizational leadership. *Administrative Sciences*, 15(2), 33.

[29] Farnese, M. L., Barbieri, B., Chirumbolo, A., Patriotta, G. (2019) Managing knowledge in organizations: a nonaka's SECI model operationalization. *Frontiers in Psychology*, 10, 2730.

[30] Teece, D. J. (2020) Hand in glove: open innovation and the dynamic capabilities framework. *Strategic Management Review*, 1(2), 233-253.

[31] Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., Verma, S. (2024) Artificial Intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*, 333(2), 627-652.

[32] Kalogiannidis, S., Kalfas, D., Papaevangelou, O., Giannarakis, G., Chatzitheodoridis, F. (2024) The role of Artificial Intelligence technology in predictive risk assessment for business continuity: a case study of Greece. *Risks*, 12(2), 19.

[33] Stanojević, D., Ćirović, V. (2020) Contribution to development of risk analysis methods by application of Artificial Intelligence techniques. *Quality and Reliability Engineering International*, 36(7), 2268-2284.