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Research on the Impact of Organizational AI Capability on Innovation Performance

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Abstract

Although artificial intelligence (AI) has become increasingly embedded in organizational innovation activities, firms still differ in their ability to convert AI investments into innovation outcomes; therefore, this study examines how AI capability influences firm innovation performance through AI-enhanced knowledge management and how information governance conditions this value creation process. Based on survey data from 416 firms that had adopted AI, this study uses SPSS to examine the effect between AI capability, knowledge acquisition, knowledge sharing, knowledge application, and the moderating role of information governance. The results show that AI capability significantly improves innovation performance and positively affects all three knowledge management processes; knowledge acquisition and knowledge sharing significantly mediate the relationship between AI capability and innovation performance, whereas the mediating effect of knowledge application is not significant, and information governance strengthens both the AI capability-innovation performance relationship and the effects of AI capability on AI-enhanced knowledge management. This study contributes to AI value creation research by shifting attention from AI adoption to AI capability building, opening the black box between AI capability and innovation performance through AI-enhanced knowledge management, and identifying information governance as an enabling condition for transforming AI capability into innovation value.

Keywords

AI Capability, Innovation Performance, AI-Enhanced Knowledge Management

1. Introduction

Artificial intelligence (AI) has become increasingly embedded in organizations. As data resources, computing power, and algorithmic tools become more accessible, firms are using AI not only for automation and prediction but also for knowledge search, decision support, product development, and process optimization. AI is no longer merely a technical tool; it is becoming a general-purpose technology that reshapes how firms generate, process, share, and apply knowledge in innovation activities (Mariani et al., 2023; Lin & Maruping, 2025). Although many firms have invested heavily in AI systems, their innovation outcomes remain delayed, uneven, or difficult to observe in the short term (Brynjolfsson et al., 2021). Therefore, the central issue is no longer whether firms adopt AI, but how firms build AI capability and transform such capability into innovation performance. AI capability refers to a firm's ability to select, orchestrate, and leverage AI-specific resources to support repeatable and reliable value creation activities (Mikalef & Gupta, 2021). As AI technologies become increasingly available in the market, competitive differences are less likely to arise from access to algorithms alone and more likely to depend on how firms integrate AI-related resources into organizational processes and capabilities.

Among these organizational processes, knowledge management is particularly important. Innovation depends fundamentally on the acquisition, recombination, sharing, and application of knowledge (Nonaka, 1994; Alavi & Leidner, 2001). AI reshapes these knowledge processes by enabling firms to identify weak signals from large-scale heterogeneous data, reduce the cost of knowledge search and communication, and embed knowledge into decisions, workflows, and routines (Jarrahi et al., 2023; Leoni et al., 2024). Nevertheless, AI-enabled knowledge processes also create new governance challenges. AI systems depend heavily on data quality, information transparency, access control, accountability, and traceability. When information ownership is unclear, data standards are inconsistent, or AI-generated outputs are difficult to explain and audit, firms may face knowledge fragmentation, low trust in AI-supported decisions, and biased or unreliable innovation inputs. In this context, information governance becomes a critical condition for realizing the innovation value of AI capability (Tallon et al., 2013).

Building on these arguments, this study investigates whether AI capability directly improves innovation performance and whether this relationship is transmitted through three AI-enhanced knowledge management processes: knowledge acquisition, knowledge sharing, and knowledge application. In addition, this study introduces information governance as a boundary condition and examines whether it strengthens the effects of AI capability on innovation performance and on the three knowledge management processes. To test the research model, this study collected survey data from 416 firms that had adopted AI. The respondents were mainly middle and senior managers, AI- or data-related managers, R&D and innovation managers.

The empirical results show that AI capability has a significant positive effect on firm innovation performance and also significantly promotes knowledge acquisition, knowledge sharing, and knowledge application. The mediation results indicate that knowledge acquisition and knowledge sharing significantly transmit the effect of AI capability on innovation performance, whereas the mediating effect of knowledge application is not significant when the three knowledge processes are examined simultaneously. The moderation results further show that information governance strengthens the positive relationship between AI capability and innovation performance, as well as the positive effects of AI capability on knowledge acquisition, knowledge sharing, and knowledge application. These findings suggest that the innovation value of AI capability depends not only on AI-related resources themselves but also on the knowledge processes and governance conditions through which these resources are transformed into innovation outcomes.

This study makes three main theoretical contributions. First, it contributes to AI capability research by shifting the focus from AI adoption to organizational capability building. It shows that AI contributes to innovation not simply because firms possess AI technologies, but because they develop the capability to integrate tangible, human, and intangible AI-related resources into organizational processes. Second, this study opens the black box between AI capability and innovation performance by identifying AI-enhanced knowledge management as a key transmission mechanism. In particular, it shows that knowledge acquisition and knowledge sharing play significant mediating roles, highlighting the importance of knowledge input and knowledge flow in AI-enabled innovation. Third, this study extends AI innovation research by introducing information governance as an enabling boundary condition. The findings show that governance does not merely constrain risk; it also strengthens the value creation process by enhancing the trustworthiness, accessibility, and controllability of AI-enabled knowledge. Overall, this study advances an integrated understanding of AI value creation by linking AI capability, knowledge management processes, information governance, and firm innovation performance.

2. Theoretical Background and Hypotheses

2.1. Resource-Based View and Information Governance

Existing research has widely employed the resource-based view (RBV) to explain performance differences among firms within the same industry. This perspective has developed an explanatory logic centered on organizational capabilities, emphasizing that capabilities are translated into performance outcomes by shaping key organizational processes (Bharadwaj, 2000; Wade & Hulland, 2004). Accordingly, studies on IT business value suggest that a single technological resource is unlikely to independently generate sustained competitive advantage. Rather, such advantage is more likely to arise from IT capability formed through the combination of technological resources and complementary organizational resources, as well as from the way this capability is embedded in business processes (Bharadwaj, 2000; Melville et al., 2004). This logic provides a useful reference for understanding capability formation in the AI context. As AI technological components become increasingly accessible, first-mover advantages at the tool level are more easily imitated, and competitive differences are more likely to stem from the deep coupling and coordinated orchestration of complementary resources such as data assets, talent structures, process routines, and organizational culture (Mikalef & Gupta, 2021). Therefore, AI capability requires organizations to integrate and deploy bundles of resources, including data, algorithms, computing power, talent, and institutional routines, rather than merely adopting AI technologies or improving the performance of isolated AI systems (Mikalef & Gupta, 2021; Weber et al., 2023).

Information governance theory originates from the renewed recognition of information as a critical organizational asset in the process of digital transformation. Its early logic is closely related to IT governance and data governance, emphasizing the use of institutionalized arrangements to clarify data- and information-related rights, responsibilities, and decision-making mechanisms (Khatri & Brown, 2010). Building on this view, Tallon et al. (2013) argue that information governance should focus on the life-cycle management of information artifacts and define it as a set of governance capabilities and organizational arrangements designed to improve information quality, information availability, and the value of information use. More specifically, information governance can be operationalized as a series of governance practices covering the entire information life cycle, strengthening the controllability, usability, and shareability of information resources through transparency, ownership, and permeability (Mikalef et al., 2020). Accordingly, the core of information governance lies in promoting the orderly flow of information within organizations and enabling value creation through clearly defined responsibility boundaries and institutional rules (Tallon et al., 2013; Mikalef et al., 2020). In the AI era, the importance of information governance has become even more pronounced, as AI systems increasingly depend on high-quality data, clear accountability boundaries, and traceable processes, while organizations simultaneously face emerging risks such as privacy leakage, bias diffusion, and ambiguous responsibility attribution (Mikalef et al., 2020). Meanwhile, the organizational application of generative AI is pushing firms to redesign platforms, processes, and collaboration structures to accommodate new tasks such as content generation, knowledge verification, and quality management. This development extends governance from the data layer to the model and content layers (Wessel et al., 2025).

2.2. AI Capability and Innovation Performance

Existing definitions of AI capability remain inconsistent. Mikalef and Gupta define AI capability as an organization's ability to select, orchestrate, and leverage AI-specific resources to support repeatable and reliable value-creating activities. This conceptualization shifts the research focus from the possession of AI technologies to resource orchestration and capability formation, and operationalizes AI capability as a higher-order construct composed of tangible resources, human resources, and intangible resources (Mikalef & Gupta, 2021). From a dynamic capability's perspective, Chen et al. define AI capability as a set of routines that integrate tangible resources, such as technologies and data, as well as intangible resources, such as coordination and organizational capabilities. They further decompose AI capability into three progressively complex sub-capabilities: sensing, predictive, and prescriptive AI capabilities (Chen et al., 2026). In this study, AI capability is conceptualized as a second-order construct composed of tangible, human, and intangible resources. It emphasizes an organization's ability to select, orchestrate, and leverage AI-related resources, thereby shaping organizational practices and enabling new value creation.

According to the resource-based view, performance differences among firms stem from the bundles of valuable and difficult-to-imitate resources and capabilities that firms possess and are able to deploy effectively (Barney, 1991). As algorithms and computing power become increasingly accessible in the market, competitive advantage is less likely to arise from the mere possession of AI components. Rather, it depends on the extent to which firms deeply couple available AI elements with proprietary data, domain-specific business knowledge, and process routines, and internalize them as organizational capabilities (Barney, 1991; Mikalef & Gupta, 2021). When such coupling is embedded in reusable cross-functional technological architectures, talent systems, and governance rules, AI capability is more likely to exhibit path dependence and causal ambiguity, thereby increasing its inimitability and providing a stable foundation for innovation activities (Berente et al., 2021). Moreover, AI capability enhances an organization's ability to acquire, identify, and analyze large volumes of heterogeneous information, enabling firms to conduct opportunity discovery, demand insight generation, and technology trajectory selection with greater quality, timeliness, and accuracy (Mikalef & Gupta, 2021). At the same time, by optimizing resource allocation, reducing exploration costs, and accelerating experimentation-learning cycles, AI capability improves firms' efficiency in screening, iterating, and diffusing innovation projects, making it more likely to be translated into observable innovation performance outcomes (Berente et al., 2021).

H1. AI capability is positively related to firm innovation performance.

2.3. AI Capability and AI-Enhanced Knowledge Management

With the rapid development of information technologies, artificial intelligence (AI) has become an important tool and method embedded in organizations' daily practices. Existing research on the impact of AI capability on knowledge management shows a clear shift from tool-based enablement to ecological integration. The central concern of this research stream is how the deep integration of AI can optimize the entire knowledge management process and ultimately enhance organizational effectiveness. Prior studies generally agree that AI technologies can significantly improve both the efficiency and quality of key knowledge management activities, including knowledge creation, storage and retrieval, sharing, and application.

The effect of AI capability on knowledge acquisition is mainly reflected in its ability to improve the breadth, depth, and timeliness of knowledge acquisition. The technical connectivity enabled by AI infrastructure expands the organizational environment that firms can observe, thereby strengthening their continuous scanning of market, technological, and operational information and broadening the range of knowledge sources (Mikalef & Gupta, 2021). Organizational AI capability also improves weak-signal detection and noise filtering, enabling firms to extract actionable knowledge cues from massive volumes of data more efficiently and thereby enhance the quality of knowledge inputs (Mühlroth et al., 2023). Through human-AI complementarity, AI capability combines machines' high-speed generation and retrieval capacity with human contextual understanding and value judgment. This makes it easier for organizations to develop actionable cognition regarding future opportunities, risks, and resource allocation, and improves the efficiency of insight generation (Fügener et al., 2022).

With regard to knowledge sharing, AI capability improves the speed and scope of knowledge sharing mainly by reducing sharing costs, enhancing matching efficiency, and improving cross-boundary comprehensibility. Through semantic search, intelligent recommendation, and conversational interaction, AI capability significantly reduces the costs of knowledge searching and expression, making knowledge easier to discover, understand, and reuse. As a result, it enhances the accessibility of knowledge and improves the efficiency and timeliness of knowledge flows across departments and positions (Jarrahi et al., 2023). When organizations possess stronger AI capability, they can more accurately match individuals' knowledge needs with relevant knowledge resources, shifting knowledge sharing from reliance on personal networks to more systematic cross-departmental knowledge connections (Mikalef & Gupta, 2021). In addition, AI capability enhances knowledge transferability through summarization, structuring, and re-expression, making tacit experience more likely to be converted into explicit knowledge that can be used by teams. This reduces cross-role communication barriers and improves the quality of knowledge sharing (Noy & Zhang, 2023; Jarrahi et al., 2023). AI capability can also strengthen the organizational network foundation for cross-regional and cross-functional knowledge sharing by facilitating inter-team collaboration, thereby increasing both the breadth and speed of knowledge sharing (Jarrahi et al., 2023).

AI capability further improves the efficiency, quality, and scalability of knowledge application by embedding knowledge into decisions and processes, enhancing consistency in organizational knowledge use, and expanding the scope of knowledge diffusion (Mikalef & Gupta, 2021; Berente et al., 2021; Jarrahi et al., 2023). It enables organizations to embed knowledge into decision-making processes in the form of models, rules, and recommendations, such as prediction, optimization, and generative assistance. In doing so, AI capability increases the actionability of knowledge in key business activities and promotes the transformation of knowledge from understanding into action (Kim et al., 2020; Cui et al., 2026; Noy & Zhang, 2023). Moreover, AI capability encodes organizational knowledge into reusable processes and automated routines, improving the consistency and scalable diffusion of knowledge application and reducing excessive dependence on individual experience (Berente et al., 2021; Lin & Maruping, 2025). Therefore, we propose the following hypotheses:

H2a. AI capability is positively related to knowledge acquisition.

H2b. AI capability is positively related to knowledge sharing.

H2c. AI capability is positively related to knowledge application.

2.4. Knowledge Management and Innovation Performance

In a competitive landscape increasingly shaped by data, algorithms, and platforms, innovation performance no longer depends solely on the scale of R&D investment. Rather, it depends more on whether organizations can transform massive volumes of heterogeneous information into interpretable, shareable, and reusable knowledge assets, and thereby develop a sustained capability for knowledge recombination (Nonaka, 1994). Against this background, AI-enhanced knowledge management can be understood as a set of organizational practices and capability configurations through which technologies such as machine learning, natural language processing, and intelligent recommendation are embedded into knowledge acquisition, sharing, and application processes. These practices improve the organization's ability to identify, encode, match, and use knowledge for decision support (Rezaei, 2025).

In the dimension of knowledge acquisition, AI transforms dispersed weak signals into structured knowledge cues through semantic extraction, pattern recognition, and automated induction from multi-source heterogeneous data. This expands the scope of opportunity recognition, reduces cognitive noise in early-stage exploration, and enables innovation activities to become more targeted and closely aligned with market problems. Prior research has also shown that stronger knowledge acquisition capability can significantly improve firm innovation performance (Jiang et al., 2022). In the dimension of knowledge sharing, AI-driven recommendation systems, knowledge graphs, and conversational knowledge services enhance knowledge visibility and cross-team accessibility. These mechanisms enable different functional units to align their understanding within a shared semantic framework and engage in cross-domain recombination, thereby transforming localized knowledge into an organizational-level combinative innovation capability. Evidence from distributed teams also indicates that high-quality collaborative knowledge sharing significantly enhances innovation performance (Xia et al., 2021). In the dimension of knowledge application, AI embeds knowledge into organizational processes in the form of prediction, simulation, and decision recommendations, enabling firms to conduct scenario analysis, rapid correction, and experience accumulation at lower experimentation costs. This improves the conversion rate from knowledge to innovation outcomes. Research in B2B contexts further suggests that AI-enabled systems promote innovation by improving decision-making performance and activating strategic agility (Liu et al., 2025). However, such benefits do not occur automatically. Knowledge application can be stably transformed into innovation returns only when organizations maintain an augmentation-oriented rather than substitution-oriented human-AI division of labor and prevent automation bias from crowding out organizational learning (Raisch & Krakowski, 2021). Accordingly, we propose the following hypotheses:

H3a. Knowledge acquisition is positively related to firm innovation performance.

H3b. Knowledge sharing is positively related to firm innovation performance.

H3c. Knowledge application is positively related to firm innovation performance.

2.5. Mediating Role of AI-Enhanced Knowledge Management

AI capability is a higher-order capability through which firms coordinate and orchestrate data, algorithms, talent, and business processes. Its effect on innovation performance often depends on knowledge management processes that transform "data-information-insights" into organizational knowledge that can be used for innovation (Alavi & Leidner, 2001). Accordingly, knowledge acquisition, knowledge sharing, and knowledge application can be regarded as three core knowledge processes through which AI capability releases its value. They correspond respectively to knowledge input, knowledge flow, and knowledge implementation, thereby constituting the key transmission mechanism through which AI capability affects innovation performance (Leoni et al., 2022).

Knowledge acquisition emphasizes the search, identification, collection, and initial assimilation of internal and external knowledge. Its core function is to expand organizational knowledge boundaries and improve the efficiency with which firms recognize and understand new knowledge. Through automated data collection, machine learning-based mining, and pattern recognition, AI capability significantly strengthens an organization's real-time sensing of markets, technologies, and customer needs, as well as its ability to capture weak signals. In this way, it improves the breadth, depth, and timeliness of knowledge inputs available for innovation (Jarrahi et al., 2023; Gama & Magistretti, 2025).

Knowledge sharing emphasizes the transfer, exchange, and diffusion of knowledge among individuals, teams, and departments. It helps break down knowledge silos and facilitates knowledge recombination (Nonaka, 1994; Alavi & Leidner, 2001). AI capability reduces the costs of knowledge encoding and communication through knowledge recommendation, semantic search, and assisted expression, thereby increasing the frequency and scope of knowledge sharing (Olan et al., 2022; Jarrahi et al., 2023).

Knowledge application emphasizes embedding acquired and shared knowledge into decision-making and business processes, transforming "what is known" into "what is done", and thereby supporting the development, experimentation, diffusion, and commercialization of innovation solutions (Alavi & Leidner, 2001; Gold et al., 2001). Through predictive analytics, intelligent decision support, and rapid experimental iteration, AI capability strengthens the organization's ability to use knowledge for opportunity recognition, solution selection, and resource allocation. It also helps move innovation activities from ideas to repeatable organizational action (Lin & Maruping, 2025). At the micro level, recent empirical studies further show that AI assistance can release the cognitive resources of knowledge workers and improve creative output or task quality, providing observable behavioral evidence for the mechanism linking knowledge application to innovation outcomes (Jiang et al., 2022; Noy & Zhang, 2023). Therefore, we propose the following hypotheses:

H4a. Knowledge acquisition mediates the relationship between AI capability and innovation performance.

H4b. Knowledge sharing mediates the relationship between AI capability and innovation performance.

H4c. Knowledge application mediates the relationship between AI capability and innovation performance.

2.6. Moderating Role of Information Governance

From the perspective of the resource-based view, whether AI capability can improve innovation performance depends on its ability to orchestrate resource bundles, such as data, algorithms, computing power, and talent, into repeatable and scalable innovation process capabilities (Mikalef & Gupta, 2021). In practice, however, this transformation depends heavily on the institutionalized foundation provided by information governance, namely the extent to which information is usable, trustworthy, and controllable. AI-enabled innovation often crosses departmental data and knowledge boundaries. Without clear rights, responsibilities, and rules, AI capability can easily become confined to local application scenarios, leading to data silos and accountability gaps, which increase trial-and-error costs and weaken innovation outputs (Vial, 2023). By contrast, when organizations establish responsibility, standards, and coordination mechanisms through structural, procedural, and relational practices, AI-enabled innovation is more likely to be organized, scaled, and continuously iterated (Papagiannidis et al., 2025; Lin & Maruping, 2025).

Information governance improves the interpretability and connectivity of data through data standards, metadata management, and the allocation of data quality responsibilities. These practices enable AI capability to generate verifiable insights and solutions more consistently, thereby improving the accuracy of innovation project selection and the quality of innovation outcomes (Vial, 2023; Volz et al., 2025). In addition, information governance clarifies decision rights and accountability chains and strengthens transparency and auditing. By enhancing the traceability and accountability of AI outputs, information governance increases managers' and employees' trust in, and willingness to adopt, AI-assisted decisions in R&D, design, and commercialization. This, in turn, accelerates the transition of innovation from exploratory experimentation to product-oriented diffusion (Papagiannidis et al., 2025; Xiong et al., 2025). Accordingly, we propose the following hypothesis:

H5. Information governance positively moderates the relationship between AI capability and innovation performance.

In the knowledge acquisition stage, AI capability can expand the boundaries of knowledge search through automated retrieval, semantic extraction, and weak-signal detection. However, the effectiveness of these functions depends heavily on data visibility, accessibility, and quality consistency. In the absence of institutionalized governance over data catalogs, metadata, and access rules, organizations may face repeated data collection, noisy inputs, and interpretive conflicts across systems. As a result, knowledge acquisition may become fast but insufficiently usable (Vial, 2023). When information governance is strong, organizations can make data resources and processing rules more transparent, clarify data responsibilities and access boundaries, and provide visible explanations of privacy and compliance risks. These practices substantially reduce knowledge acquisition friction and improve the credibility of knowledge inputs, thereby strengthening the positive effect of AI capability on knowledge acquisition (Dehling & Sunyaev, 2024; Alavi et al., 2024).

In the knowledge sharing stage, AI capability improves knowledge accessibility through enterprise intelligent search, recommendation systems, and question-and-answer systems. However, the core bottleneck of knowledge sharing often lies not in technical connectivity, but in trust, ownership, and semantic consistency across departmental boundaries. Weak governance may force AI-based distribution mechanisms to remain confined within local knowledge repositories, or lead organizations to adopt conservative sharing practices because of compliance uncertainty. This weakens the breadth of knowledge sharing and the depth of knowledge recombination (Vial, 2023). When information governance is more developed, organizations can establish enforceable arrangements that balance boundary permeability and security control. Through layered access authorization, data anonymization, and responsibility tracking, firms can improve the controllability of knowledge sharing. At the same time, knowledge coding standards and master data standards reduce semantic drift, making AI-driven knowledge distribution more likely to cross organizational boundaries and generate shared understanding. In this way, information governance amplifies the positive effect of AI capability on knowledge sharing (Papagiannidis et al., 2025; Leoni et al., 2022).

In the knowledge application stage, the advantage of AI capability lies in embedding knowledge into decision-making and execution in the form of model-based recommendations, rules, or process automation. Yet knowledge application relies most strongly on traceability and accountability. Insufficient governance may result in unclear sources of recommendations, broken accountability chains, and unauditable decision processes, ultimately leading to non-use, symbolic use, or risk spillovers (Grote et al., 2026; Rezaei, 2025). By contrast, information governance clarifies decision rights and the boundaries of human–AI division of labor, establishes governance mechanisms that align control with accountability, and strengthens recording, auditing, and feedback loops across the data and model life cycle. These arrangements enhance organizational trust in AI recommendations and increase the likelihood of their adoption, allowing AI capability to be more smoothly transformed into improved knowledge application efficiency and routinized organizational practices. In doing so, information governance helps avoid performance paradoxes arising from tensions between automation and augmentation (Raisch & Krakowski, 2021; Berente et al., 2021). Accordingly, this study proposes the following hypotheses:

H6a. Information governance positively moderates the relationship between AI capability and knowledge acquisition.

H6b. Information governance positively moderates the relationship between AI capability and knowledge sharing.

H6c. Information governance positively moderates the relationship between AI capability and knowledge application.

In summary, the theoretical research model of this study is presented in Figure 1.

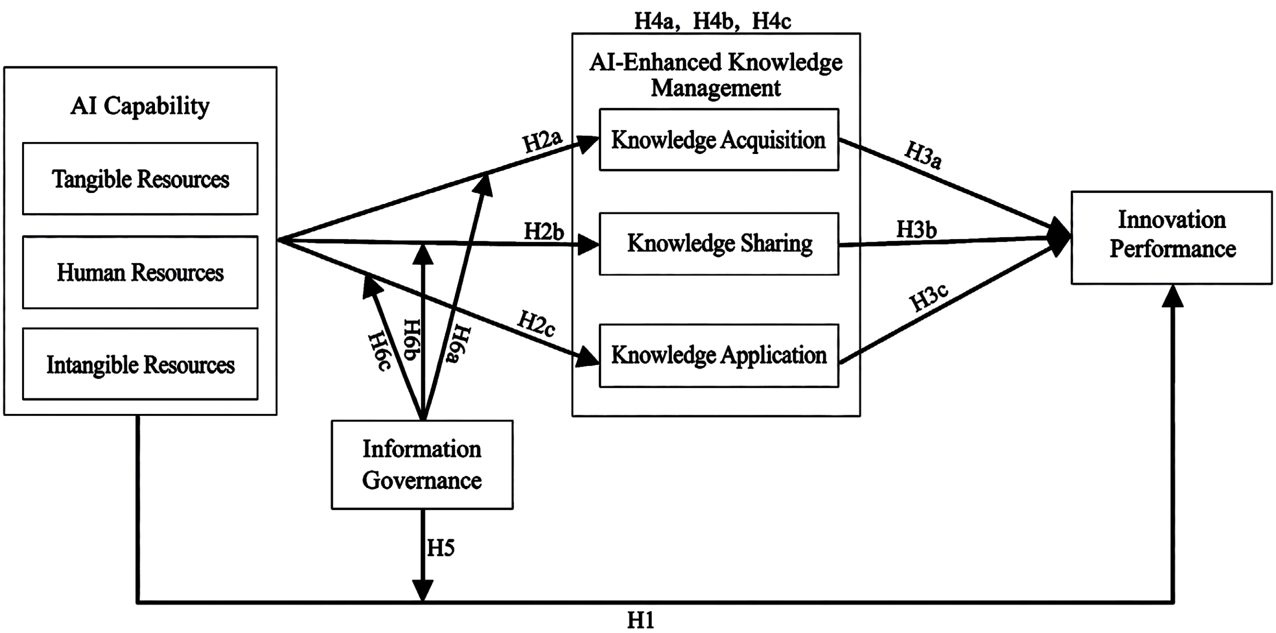

Figure 1. Theoretical framework.

3. Research Method

3.1. Sample and Data Collection

This study collected data through a questionnaire survey. The target respondents were Chinese firms that had adopted artificial intelligence applications in their core business, R&D, or management processes. To ensure that respondents could provide accurate evaluations of firm AI capability, knowledge management processes, information governance practices, and innovation performance, the questionnaire was mainly directed to middle and senior managers, AI- or data-related managers, R&D and innovation managers, and key business personnel familiar with firms' digitalization and knowledge management practices. The questionnaire was distributed online. At the beginning of the questionnaire, the research purpose and academic use of the data were clearly explained to reduce respondents' concerns. To reduce potential common method bias, this study adopted several procedural remedies. Specifically, respondents were assured of anonymity when completing the questionnaire. In addition, the questionnaire items were randomly ordered and mixed to prevent respondents from inferring the research purpose from the sequence of the items. Firms were recruited through industry associations, professional networks, MBA/EMBA alumni networks, and online business communities. After excluding incomplete responses, patterned responses, and samples that did not meet the research requirements, 416 valid questionnaires were retained for the final analysis.

3.2. Measures

All core variables in this study were measured using established scales, with appropriate modifications made to fit the AI application context. A five-point Likert scale was used, ranging from 1 = "strongly disagree" to 5 = "strongly agree". The independent variable is AI capability. Following Mikalef and Gupta (2021), AI capability was measured in terms of tangible resources, human resources, and intangible resources, capturing firms' ability to integrate, orchestrate, and leverage AI-related resources. The dependent variable is innovation performance. Drawing on Wang and Lin (2012) and Qiao et al. (2025a), innovation performance was measured by assessing firms' performance relative to competitors in product innovation, process innovation, and innovation outcomes. The mediating variable is AI-enhanced knowledge management, which includes three dimensions: knowledge acquisition, knowledge sharing, and knowledge application. These dimensions were measured mainly based on established knowledge management scales. The moderating variable is information governance. Following Mikalef et al. (2020), information governance was measured by assessing firms' governance practices in information transparency, responsibility allocation, access control, and rule-based information use. In addition, this study controlled for factors that may affect innovation performance, including firm size, firm age, ownership type, industry type, respondent position, and work experience.

3.3. Reliability, Validity, and Common Method Bias

SPSS was used to conduct the statistical analyses in this study. First, descriptive statistics, correlation analysis, reliability analysis, and validity analysis were performed to assess data quality and examine the preliminary relationships among the variables. Second, regression analysis was used to test the direct effects of AI capability on innovation performance, knowledge acquisition, knowledge sharing, and knowledge application. Third, the Bootstrap method was used to examine the mediating effects of the three dimensions of knowledge management in the relationship between AI capability and innovation performance. Finally, interaction terms were constructed to test the moderating effect of information governance, thereby assessing whether information governance strengthens the effects of AI capability on innovation performance and knowledge management processes.

Reliability was first assessed using Cronbach's alpha. The results show that the Cronbach's alpha values for AI capability, innovation performance, AI-enhanced knowledge management, and information governance were 0.941, 0.897, 0.935, and 0.912, respectively, all exceeding the commonly accepted threshold of 0.70. This indicates that the scales have good internal consistency. Exploratory factor analysis was then conducted to examine construct validity. The results show that the KMO value was 0.929, and Bartlett's test of sphericity was significant (χ^2 = 11061.089, df = 595, $p < 0.001$), indicating that the data were suitable for factor analysis. Six factors were extracted, with a cumulative variance explanation rate of 72.747%, suggesting good construct validity. In addition, the first unrotated factor explained 28.219% of the variance, which is below the empirical threshold of 40%. This indicates that common method bias does not pose a serious threat in this study.

4. Results

4.1. Descriptive Statistics and Correlations

Table 1 reports the means, standard deviations, and correlation coefficients of the core variables. As shown in Table 1, AI capability is significantly and positively correlated with innovation performance (r = 0.227, $p < 0.001$), knowledge acquisition (r = 0.294, $p < 0.001$), knowledge sharing (r = 0.272, $p < 0.001$), and knowledge application (r = 0.256, $p < 0.001$). Knowledge acquisition, knowledge sharing, and knowledge application are also significantly and positively correlated with innovation performance, with correlation coefficients of 0.329, 0.321, and 0.293, respectively, all reaching the 0.001 significance level. These results provide preliminary support for further testing the relationships among the variables.

Table 1. Descriptive statistics and correlations.

Variable	M	SD	1	2	3	4	5	6
1. AIC	2.994	1.158	1					
2. IP	3.010	1.236	0.227***	1				
3. KAC	2.999	1.261	0.294***	0.329***	1			
4. KS	2.997	1.228	0.272***	0.321***	0.469***	1		
5. KAP	3.010	1.256	0.256***	0.293***	0.512***	0.448***	1	
6. IG	3.013	1.101	0.070	0.084	0.027	0.062	0.024	1

Note. N = 416. AIC = AI capability; IP = innovation performance; KAC = knowledge acquisition; KS = knowledge sharing; KAP = knowledge application; IG = information governance. ***$p < 0.001$.

4.2. Hypothesis Testing

To examine the effects of AI capability on knowledge management processes and innovation performance, as well as the effects of knowledge management processes on innovation performance, this study conducted hierarchical regression analyses after controlling for relevant variables. As shown in Table 2, AI capability has significant positive effects on knowledge acquisition (B = 0.309, β = 0.292, $p < 0.001$), knowledge sharing (B = 0.286, β = 0.263, $p < 0.001$), knowledge application (B = 0.279, β = 0.261, $p < 0.001$), and innovation performance (B = 0.253, β = 0.232, $p < 0.001$). Meanwhile, knowledge acquisition (B = 0.342, β = 0.333, $p < 0.001$), knowledge sharing (B = 0.337, β = 0.336, $p < 0.001$), and knowledge application (B = 0.296, β = 0.290, $p < 0.001$) all have significant positive effects on innovation performance. These results indicate that AI capability not only directly enhances firm innovation performance but also significantly promotes knowledge acquisition, knowledge sharing, and knowledge application. In addition, knowledge management processes play a significant role in improving innovation performance.

Table 2. Results of main-effect regression analyses.

Path	B	SE	beta	t	Delta F
AIC → KAC	0.309***	0.050	0.292	6.124	37.504
AIC → KS	0.286***	0.051	0.263	5.555	30.861
AIC → KAP	0.279***	0.051	0.261	5.434	29.531
AIC → IP	0.253***	0.053	0.232	4.790	22.943
KAC → IP	0.342***	0.048	0.333	7.131	50.850
KS → IP	0.337***	0.048	0.336	7.096	50.348
KAP → IP	0.296***	0.048	0.290	6.113	37.368

Note. N = 416. AIC = AI capability; IP = innovation performance; KAC = knowledge acquisition; KS = knowledge sharing; KAP = knowledge application. ***$p < 0.001$.

This study used PROCESS Model 4 to examine the mediating roles of knowledge acquisition, knowledge sharing, and knowledge application in the relationship between AI capability and innovation performance, with the control variables included in the model. As shown in Table 3, AI capability has significant positive effects on knowledge acquisition (B = 0.309, $p < 0.001$), knowledge sharing (B = 0.286, $p < 0.001$), and knowledge application (B = 0.279, $p < 0.001$). After controlling for AI capability and the other mediators, knowledge acquisition (B = 0.174, $p < 0.01$) and knowledge sharing (B = 0.184, $p < 0.001$) have significant positive effects on innovation performance, whereas the effect of knowledge application on innovation performance is not significant (B = 0.093, $p > 0.05$). The Bootstrap results further show that the indirect effects of AI capability on innovation performance through knowledge acquisition and knowledge sharing are significant, as their confidence intervals do not include zero. However, the indirect effect through knowledge application is not significant. Therefore, knowledge acquisition and knowledge sharing play significant mediating roles between AI capability and innovation performance, whereas the mediating role of knowledge application is not supported.

Table 3. Bootstrap tests of mediation effects.

Mediating path	Indirect effect	Boot SE	95% Boot CI
AIC → KAC → **IP**	0.054	0.021	[0.017, 0.097]
AIC → KS → **IP**	0.053	0.019	[0.020, 0.095]
AIC → KAP → **IP**	0.026	0.017	[−0.006, 0.063]
Total indirect effect	0.132	0.029	[0.079, 0.193]

Note. N = 416. AIC = AI capability; IP = innovation performance; KAC = knowledge acquisition; KS = knowledge sharing; KAP = knowledge application. Bootstrap sample size = 5000.

In addition, the total effect of AI capability on innovation performance is significant (B = 0.253, $p < 0.001$). After knowledge acquisition, knowledge sharing, and knowledge application are included in the model, the direct effect of AI capability on innovation performance remains significant (B = 0.121, $p < 0.05$). This indicates that knowledge management processes play a partial mediating role in the relationship between AI capability and innovation performance.

This study tested the moderating effects by constructing interaction terms between AI capability and information governance. As shown in Table 4, the interaction term between AI capability and information governance has a significant positive effect on innovation performance (B = 0.451, $p < 0.001$), indicating that information governance positively moderates the relationship between AI capability and innovation performance. Further analysis shows that the interaction term also has significant positive effects on knowledge acquisition (B = 0.448, $p < 0.001$), knowledge sharing (B = 0.479, $p < 0.001$), and knowledge application (B = 0.481, $p < 0.001$). These results suggest that information governance strengthens the positive effects of AI capability on knowledge management processes.

Table 4. Moderating effects of information governance.

Dependent variable	Interaction B	SE	beta	t
IP	0.451***	0.043	0.453	10.519
KAC	0.448***	0.041	0.463	11.014
KS	0.479***	0.041	0.483	11.754
KAP	0.481***	0.041	0.493	11.822

Note. N = 416. AIC = AI capability; IP = innovation performance; KAC = knowledge acquisition; KS = knowledge sharing; KAP = knowledge application. ***$p < 0.001$.

Table 5 further presents the moderating effect of information governance on the relationship between AI capability and the outcome variables. The simple slope analysis indicates that, compared with low levels of information governance, AI capability exerts stronger positive effects on innovation performance, knowledge acquisition, knowledge sharing, and knowledge application under high levels of information governance. Specifically, when information governance is high, AI capability has stronger positive effects on innovation performance (B = 0.730, $p < 0.001$), knowledge acquisition (B = 0.789, $p < 0.001$), knowledge sharing (B = 0.796, $p < 0.001$), and knowledge application (B = 0.793, $p < 0.001$). In contrast, under low levels of information governance, these relationships become significantly negative. These findings suggest that higher levels of information governance enable organizations to better coordinate and regulate the application of AI capability, thereby strengthening its positive effects on innovation performance and knowledge management processes, further supporting the positive moderating role of information governance.

Table 5. Simple slope estimates at different levels of information governance.

Dependent variable	IG level	Simple slope B	SE	t
IP	Low IG (−1 SD)	−0.262***	0.067	−3.883
IP	Centered IG (0)	0.234***	0.047	4.998
IP	High IG (+1 SD)	0.730***	0.066	11.133
KAC	Low IG (−1 SD)	−0.198**	0.064	−3.089
KAC	Centered IG (0)	0.295***	0.045	6.636
KAC	High IG (+1 SD)	0.789***	0.062	12.66
KS	Low IG (−1 SD)	−0.258***	0.064	−4.033
KS	Centered IG (0)	0.269***	0.045	6.024
KS	High IG (+1 SD)	0.796***	0.062	12.754
KAP	Low IG (−1 SD)	−0.265***	0.064	−4.138
KAP	Centered IG (0)	0.264***	0.045	5.941
KAP	High IG (+1 SD)	0.793***	0.062	12.744

Note. ** $p < 0.01$, *** $p < 0.001$.

To further illustrate the moderating effects, Figure 2 presents the interaction plots, showing that the positive effects of AI capability on innovation performance and knowledge management processes are stronger when information governance is high rather than low. As shown in Figure 3, when information governance is high, knowledge acquisition, knowledge application, and knowledge sharing all increase as AI capability rises. In contrast, when information governance is low, these three knowledge management processes show a slight downward trend, indicating that information governance strengthens the positive effect of AI capability on AI-enhanced knowledge management.

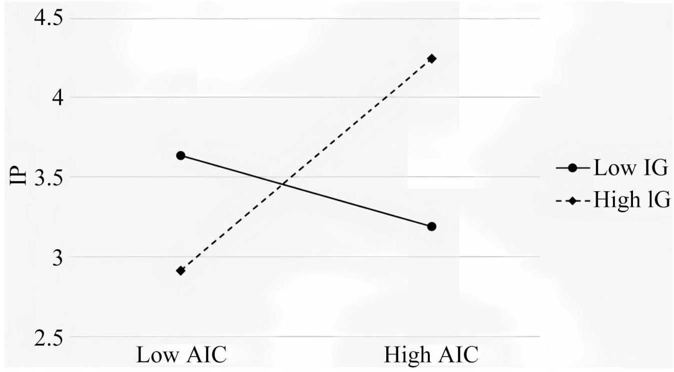

Figure 2. Moderating effect of information governance on AI capability and innovation performance.

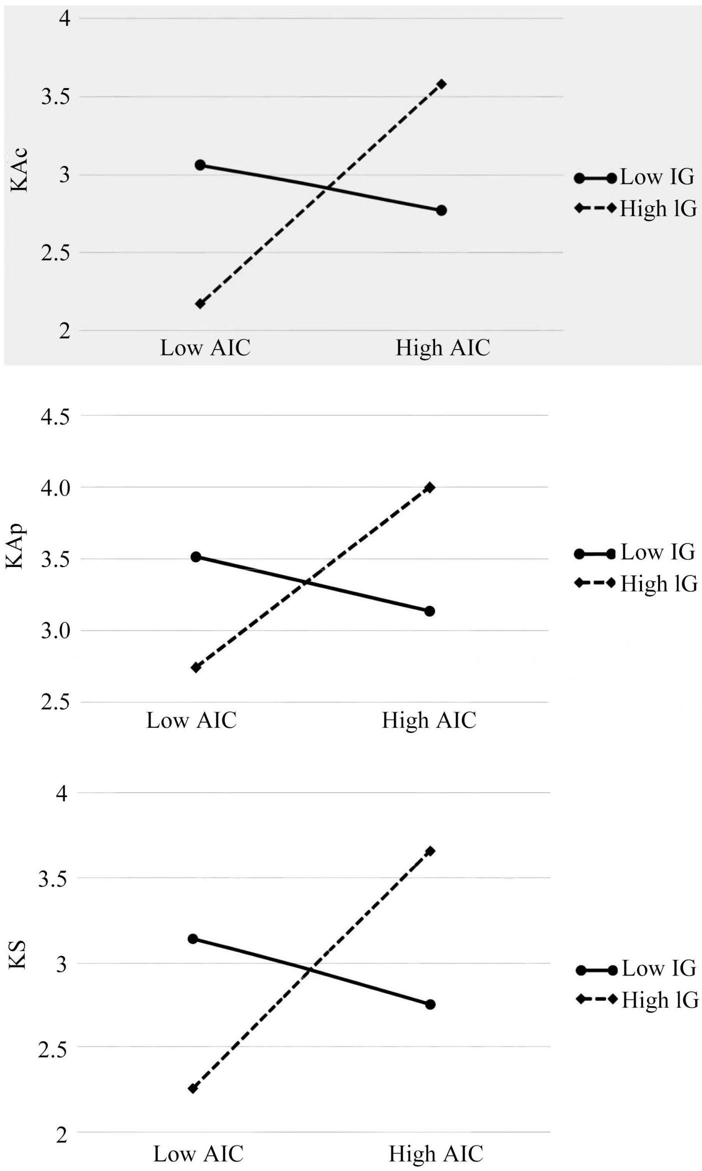

Figure 3. Moderating effect of information governance on AI capability and AI-enhanced knowledge management.

5. Discussion

5.1. Key Findings

This study shows that AI capability significantly improves innovation performance and positively affects knowledge acquisition, knowledge sharing, and knowledge application, supporting the view that AI creates value not through technology adoption alone, but through the organizational orchestration of AI-related resources and routines (Mikalef & Gupta, 2021). The mediation results indicate that knowledge acquisition and knowledge sharing significantly transmit the effect of AI capability on innovation performance, suggesting that AI capability contributes to innovation mainly by broadening knowledge search and accelerating knowledge flow and recombination across organizational boundaries (Alavi & Leidner, 2001).

However, the mediating effect of knowledge application is not significant when the three knowledge processes are examined simultaneously. This does not mean that knowledge application is unimportant, because its main effect on innovation performance is significant. Rather, it suggests that knowledge application is a more downstream and condition-dependent process: transforming AI-generated knowledge into innovation outcomes requires decision routines, absorptive capacity, implementation capability, human-AI collaboration, and governance support (Raisch & Krakowski, 2021; Jarrahi et al., 2023). Without these complementary conditions, AI-enabled knowledge application may remain at the level of technical use or decision assistance and may not be fully converted into observable innovation performance.

The moderation results further show that information governance strengthens the relationship between AI capability and innovation performance, as well as the effects of AI capability on knowledge acquisition, knowledge sharing, and knowledge application. This indicates that information governance acts not only as a control mechanism but also as an enabling mechanism by improving information quality, transparency, accountability, and trust in AI-supported knowledge use (Khatri & Brown, 2010; Tallon et al., 2013; Mikalef et al., 2020). Overall, the findings suggest that AI capability generates innovation value through a capability-knowledge-governance mechanism, in which knowledge acquisition and knowledge sharing are the more direct transmission channels, while knowledge application requires stronger complementary organizational conditions.

5.2. Theoretical Contributions

This study makes three theoretical contributions. First, it advances AI capability research by shifting attention from AI adoption to the organizational capability formed through the integration of tangible, human, and intangible resources. Prior research suggests that digital and AI technologies create value only when they are combined with complementary organizational resources (Bharadwaj, 2000; Melville et al., 2004; Mikalef & Gupta, 2021). This study provides empirical evidence for this capability-based view in the context of firm innovation performance.

Second, this study opens the black box between AI capability and innovation performance by identifying AI-enhanced knowledge management as a key transmission mechanism. The results show that knowledge acquisition and knowledge sharing are particularly important in converting AI capability into innovation performance. This finding enriches the knowledge-based explanation of AI value creation and clarifies that AI-related resources must be transformed into knowledge inputs and knowledge flows before they generate innovation outcomes (Grant, 1996; Alavi & Leidner, 2001; Leoni et al., 2022).

Third, this study introduces information governance as a critical boundary condition. By showing that information governance strengthens the capability-knowledge-performance chain, this study extends AI innovation research from a technology-centered perspective to an integrated perspective that combines capability building, knowledge processes, and governance arrangements. This result also contributes to information governance research by showing that governance can operate as an enabling mechanism rather than only as a control mechanism (Tallon et al., 2013; Mikalef et al., 2020).

5.3. Practical Implications

The findings offer several implications for managers. First, firms should not treat AI investment as a narrow technology procurement project. Instead, they should build AI capability by coordinating investments in data infrastructure, AI talent, organizational routines, and cross-functional collaboration. AI systems are more likely to support innovation when they are embedded in business processes and connected to organizational knowledge bases.

Second, firms should focus on improving knowledge acquisition and knowledge sharing mechanisms. AI-generated insights can create innovation value only when they are effectively identified, interpreted, transferred, and recombined across organizational units. Managers should therefore use AI not only to automate tasks but also to expand search, improve knowledge visibility, and support cross-functional problem solving.

Third, firms need to strengthen information governance by clarifying information ownership, access rights, accountability mechanisms, and transparency rules. Strong information governance can reduce uncertainty, improve trust in AI-supported decision-making, and enhance the reliability of AI-enabled innovation activities. This is particularly important when AI systems are used in R&D, product design, customer analysis, and other innovation-related domains.

5.4. Limitations and Future Research

This study has several limitations. First, the data were collected using a questionnaire survey, which limits causal inference. Future research could use longitudinal or multi-source data to further verify the causal relationships among AI capability, knowledge management, information governance, and innovation performance.

Second, this study examines knowledge acquisition, knowledge sharing, and knowledge application as parallel mediating mechanisms. Future research may explore their sequential relationships, such as whether AI capability first enhances knowledge acquisition, which then promotes knowledge sharing and subsequent knowledge application.

Third, the non-significant mediating effect of knowledge application suggests that the transformation from knowledge application to innovation outcomes may depend on additional organizational conditions. Future studies could examine the roles of absorptive capacity, strategic agility, human-AI collaboration routines, implementation capability, and organizational learning climate. Fourth, this study focuses on firm-level innovation performance. Future research could extend the model to team-level innovation, employee creativity, or project-level innovation outcomes.

6. Conclusion

This study examines how AI capability affects firm innovation performance and clarifies the mediating role of AI-enhanced knowledge management and the moderating role of information governance. Based on survey data from 416 Chinese firms, the findings show that AI capability significantly improves innovation performance and enhances knowledge acquisition, knowledge sharing, and knowledge application. Knowledge acquisition and knowledge sharing significantly mediate the relationship between AI capability and innovation performance, while knowledge application does not show a significant mediating effect when the three knowledge processes are tested simultaneously. Information governance strengthens both the direct relationship between AI capability and innovation performance and the effects of AI capability on the three knowledge management processes. Overall, the study indicates that the innovation value of AI capability depends not only on AI-related resources but also on the knowledge processes and governance conditions that enable those resources to be transformed into innovation outcomes.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues1,2. *MIS Quarterly, 25,* 107-136. https://doi.org/10.2307/3250961

Alavi, M., Leidner, D. E., & Mousavi, R. (2024). Knowledge Management Perspective of

Generative Artificial Intelligence. *Journal of the Association for Information Systems, 25,* 1-12. https://doi.org/10.17705/1jais.00859

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management, 17,* 99-120. https://doi.org/10.1177/014920639101700108

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing Artificial Intelligence. *MIS Quarterly, 45,* 1433-1450. https://doi.org/10.25300/misq/2021/16274

Bharadwaj, A. S. (2000). A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation1. *MIS Quarterly, 24,* 169-196. https://doi.org/10.2307/3250983

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The Productivity J-Curve: How Intangibles Complement General Purpose Technologies. *American Economic Journal: Macroeconomics, 13,* 333-372. https://doi.org/10.1257/mac.20180386

Chen, R., Li, Z., Yang, G., Li, W., & Guo, Z. (2026). Exploring How Artificial Intelligence Capabilities Impact Corporate Sustainability Performance: Insights from Chinese Manufacturing Firms. *Technovation, 149,* 103429. https://doi.org/10.1016/j.technovation.2025.103429

Cui, M., Li, W., & Kamoche, K. (2026). Building Trust in Decision-Support Artificial Intelligence: A Boundary Spanning Perspective. *Information Systems Journal, 36,* 435-456. https://doi.org/10.1111/isj.70015

Dehling, T., & Sunyaev, A. (2024). A Design Theory for Transparency of Information Privacy Practices. *Information Systems Research, 35,* 956-977. https://doi.org/10.1287/isre.2019.0239

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2022). Cognitive Challenges in Human-Artificial Intelligence Collaboration: Investigating the Path toward Productive Delegation. *Information Systems Research, 33,* 678-696. https://doi.org/10.1287/isre.2021.1079

Gama, F., & Magistretti, S. (2025). Artificial Intelligence in Innovation Management: A Review of Innovation Capabilities and a Taxonomy of AI Applications. *Journal of Product Innovation Management, 42,* 76-111. https://doi.org/10.1111/jpim.12698

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge Management: An Organizational Capabilities Perspective. *Journal of Management Information Systems, 18,* 185-214. https://doi.org/10.1080/07421222.2001.11045669

Grant, R. M. (1996). Toward a Knowledge-Based Theory of the Firm. *Strategic Management Journal, 17,* 109-122. https://doi.org/10.1002/smj.4250171110

Grote, G., Parker, S. K., & Crowston, K. (2026). Taming Artificial Intelligence: A Theory of Control-Accountability Alignment among AI Developers and Users. *Academy of Management Review, 51,* 278-299. https://doi.org/10.5465/amr.2023.0117

Jarrahi, M. H., Askay, D., Eshraghi, A., & Smith, P. (2023). Artificial Intelligence and Knowledge Management: A Partnership between Human and AI. *Business Horizons, 66,* 87-99. https://doi.org/10.1016/j.bushor.2022.03.002

Jiang, W., Yang, H., & Liu, D. (2022). Innovation Ecosystem Stability and Enterprise Innovation Performance: The Mediating Effect of Knowledge Acquisition. *Journal of Knowledge Management, 26,* 378-400. https://doi.org/10.1108/jkm-04-2022-0275

Khatri, V., & Brown, C. V. (2010). Designing Data Governance. *Communications of the ACM, 53,* 148-152. https://doi.org/10.1145/1629175.1629210

Kim, B., Park, J., & Suh, J. (2020). Transparency and Accountability in AI Decision Support: Explaining and Visualizing Convolutional Neural Networks for Text Information. *Decision Support Systems, 134,* Article 113302.

https://doi.org/10.1016/j.dss.2020.113302

Leoni, L., Ardolino, M., El Baz, J., Gueli, G., & Bacchetti, A. (2022). The Mediating Role of Knowledge Management Processes in the Effective Use of Artificial Intelligence in Manufacturing Firms. *International Journal of Operations & Production Management, 42,* 411-437. https://doi.org/10.1108/ijopm-05-2022-0282

Leoni, L., Gueli, G., Ardolino, M., Panizzon, M., & Gupta, S. (2024). AI-Empowered KM Processes for Decision-Making: Empirical Evidence from Worldwide Organisations. *Journal of Knowledge Management, 28,* 320-347. https://doi.org/10.1108/jkm-03-2024-0262

Lin, Y., & Maruping, L. M. (2025). Organizing for AI Innovation: Insights from an Empirical Exploration of U.S. Patents. *MIS Quarterly, 49,* 1095-1122. https://doi.org/10.25300/misq/2025/18765

Liu, Y. D., Zhang, J. Z., Zheng, J., & Kamal, M. M. (2025). Artificial Intelligence-Enabled Systems and Innovation in B2B Firms: The Role of Strategic Agility and Decision-Making Performance. *Industrial Marketing Management, 127,* 164-174. https://doi.org/10.1016/j.indmarman.2025.04.003

Mariani, C., & Mancini, M. (2025). Harnessing AI for Value: Examining the Impact of AI Capabilities and the Mediating Role of Organizational Agility on Project Value Proposition. *International Journal of Managing Projects in Business, 18,* 112-143. https://doi.org/10.1108/ijmpb-03-2025-0068

Mariani, M. M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial Intelligence in Innovation Research: A Systematic Review, Conceptual Framework, and Future Research Directions. *Technovation, 122,* Article 102623. https://doi.org/10.1016/j.technovation.2022.102623

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information Technology and Organizational Performance: An Integrative Model of IT Business Value1. *MIS Quarterly, 28,* 283-322. https://doi.org/10.2307/25148636

Mikalef, P., & Gupta, M. (2021). Artificial Intelligence Capability: Conceptualization, Measurement Calibration, and Empirical Study on Its Impact on Organizational Creativity and Firm Performance. *Information & Management, 58,* Article 103434. https://doi.org/10.1016/j.im.2021.103434

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2020). The Role of Information Governance in Big Data Analytics Driven Innovation. *Information & Management, 57,* Article 103361. https://doi.org/10.1016/j.im.2020.103361

Mühlroth, C., Kölbl, L., & Grottke, M. (2023). Innovation Signals: Leveraging Machine Learning to Separate Noise from News. *Scientometrics, 128,* 2649-2676. https://doi.org/10.1007/s11192-023-04672-y

Nakash, M., & Bolisani, E. (2025). The Transformative Impact of AI on Knowledge Management Processes. *Business Process Management Journal, 31,* 124-147. https://doi.org/10.1108/bpmj-11-2024-1137

Nonaka, I. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Organization Science, 5,* 14-37. https://doi.org/10.1287/orsc.5.1.14

Noy, S., & Zhang, W. (2023). Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence. *Science, 381,* 187-192. https://doi.org/10.1126/science.adh2586

Olan, F., Arakpogun, E. O., Suklan, J., Nakpodia, F., Damij, N., & Jayawickrama, U. (2022). Artificial Intelligence and Knowledge Sharing: Contributing Factors to Organizational Performance. *Journal of Business Research, 145,* 605-615. https://doi.org/10.1016/j.jbusres.2022.03.008

Papagiannidis, E., Mikalef, P., & Conboy, K. (2025). Responsible Artificial Intelligence Governance: A Review and Research Framework. *The Journal of Strategic Information Systems, 34,* Article 101885. https://doi.org/10.1016/j.jsis.2024.101885

Qiao, S., Liu, Z., Wu, J., Guo, Z., & Wu, H. (2025a). Generative AI on Innovation Performance of Construction Enterprises: A Knowledge-Based Dynamic Capabilities Perspective. *Journal of Engineering and Technology Management, 76,* Article 101871. https://doi.org/10.1016/j.jengtecman.2025.101871

Qiao, S., Liu, Z., Wu, J., Ma, Y., Guo, Z., & Wu, H. (2025b). Generative AI on Innovation Performance of Construction Enterprises: The Role of Knowledge-Based Dynamic Capabilities and Enterprise AI Capabilities. *Engineering, Construction and Architectural Management, 33,* 7274-7295. https://doi.org/10.1108/ecam-01-2025-0051

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation-Augmentation Paradox. *Academy of Management Review, 46,* 192-210. https://doi.org/10.5465/amr.2018.0072

Rezaei, M. (2025). Artificial Intelligence in Knowledge Management: Identifying and Addressing the Key Implementation Challenges. *Technological Forecasting and Social Change, 217,* Article 124183. https://doi.org/10.1016/j.techfore.2025.124183

Tallon, P. P., Ramirez, R. V., & Short, J. E. (2013). The Information Artifact in IT Governance: Toward a Theory of Information Governance. *Journal of Management Information Systems, 30,* 141-178. https://doi.org/10.2753/mis0742-1222300306

Vial, G. (2023). Data Governance and Digital Innovation: A Translational Account of Practitioner Issues for IS Research. *Information and Organization, 33,* Article 100450. https://doi.org/10.1016/j.infoandorg.2023.100450

Volz, F., Münch, C., Lohmüller, M., & Küffner, C. (2025). From Data Jungle to Data Governance in Digital Ecosystems: Empirical Evidence from a Multiple Holistic Case Study. *Journal of Business Research, 201,* Article 115747. https://doi.org/10.1016/j.jbusres.2025.115747

Wade, M., & Hulland, J. (2004). Review: The Resource-Based View and Information Systems Research: Review, Extension, and Suggestions for Future Research1. *MIS Quarterly, 28,* 107-142. https://doi.org/10.2307/25148626

Wang, C.-H., & Lin, H.-E. (2012). Understanding Innovation Performance and Its Antecedents: A Socio-Cognitive Model. *Journal of Engineering and Technology Management, 29,* 210-225. https://doi.org/10.1016/j.jengtecman.2012.01.001

Weber, M., Engert, M., Schaffer, N., Weking, J., & Krcmar, H. (2023). Organizational Capabilities for AI Implementation—Coping with Inscrutability and Data Dependency in AI. *Information Systems Frontiers, 25,* 1549-1569. https://doi.org/10.1007/s10796-022-10297-y

Wessel, M., Adam, M., Benlian, A., Majchrzak, A., & Thies, F. (2025). Generative AI and Its Transformative Value for Digital Platforms. *Journal of Management Information Systems, 42,* 346-369. https://doi.org/10.1080/07421222.2025.2487315

Xia, H., Li, J., Weng, J., Zhang, Z., & Gao, Y. (2021). Collaborative Knowledge Sharing in Global Distributed Teams: Antecedents of Innovation Performance. *Journal of Knowledge Management, 25,* 2523-2539. https://doi.org/10.1108/jkm-10-2020-0763

Xiong, M., Xu, H., Ji, J., Zuo, R., Wang, Y., & Olya, H. (2025). Responsible Artificial Intelligence Attention and Firm Innovation: An Attention-Based View. *Journal of Product Innovation Management, 43,* 186-214. https://doi.org/10.1111/jpim.70015

Appendix

The table below provides the measurement items for the variables.

Construct	Items	References
AI capabilities	We have access to a vast amount of data for analysis, including unstructured or rapidly changing data. This information is organized in data warehouses to facilitate sharing among business units. We have adopted cloud-based services for data processing, enabling the use of APIs, such as Microsoft Cognitive Services and Google Cloud Vision, for carrying out AI and machine learning tasks. We have the processing power required to support AI applications, such as distributed computing and GPUs, as well as the necessary network infrastructure, such as corporate networks. We have invested in scalable data storage infrastructures and state-of-the-art end-to-end data security. Our AI initiatives are adequately funded and supported by dedicated teams. Our data scientists or consultants are proficient in utilizing AI technologies, including machine learning, natural language processing, and deep learning. Additionally, they are capable of managing data analysis, processing, and security. We are hiring experienced data scientists specializing in AI or relying on external IT consultants. Our managers understand the importance of AI initiatives, and they collaborate with data scientists to identify opportunities and risks associated with such projects. Our departments collaborate closely, sharing goals, information, and resources. We are able to anticipate potential organizational resistance to change. We respond in three ways: communicating the reasons for the change, engaging in process re-engineering, and ensuring senior management commitment to new values.	Mikalef & Gupta (2021); Mariani & Mancini (2025)
Innovation performance	By using AI in the innovation process, our company can develop new products, new technologies, new processes, and new services more quickly. By using AI in the innovation process, our new products, new technologies, new processes, and new services can be quickly recognized and adopted by the market. By using AI in the innovation process, our new products, new technologies, new processes, and new services can generate higher profits.	Qiao et al. (2025b)

Continued

AI-enhanced knowledge management	With the help of AI technologies, we identify innovative ideas for products or services. By relying on AI technologies, we identify new business opportunities. Based on AI simulation models, we predict future trends in the organization's professional domain. Through AI technologies, we automatically extract lessons learned from various organizational activities. With the help of AI technologies, we conduct comparative analyses of competitors and generate new knowledge related to the organization's competitive advantage. AI-driven search facilitates the retrieval of knowledge entries and reduces retrieval time. By relying on advanced AI algorithms, employees can automatically obtain relevant knowledge in a personalized manner. With the help of AI technologies, the efficiency of knowledge flow among employees within the organization is improved. By relying on AI technologies, collaboration among teams across different departments or geographic locations is promoted. With the help of AI technologies, a positive knowledge-sharing culture is cultivated. AI-driven decision support systems help the organization make informed decisions by analyzing alternatives and evaluating decision outcomes. Based on the analysis of work patterns, AI machine learning contributes to the improvement of organizational performance. Employees receive advice from AI-based robots on how to use the organization's existing knowledge to complete routine work tasks. With the help of AI technologies, existing knowledge is used to ensure business continuity in emergencies and crisis situations. With the help of AI technologies, accumulated knowledge is analyzed to prevent recurring failures and errors.	Nakash & Bolisani (2025)
Information governance	Our company has clearly identified key IT or AI and non-IT or non-AI decision makers responsible for data ownership, value analysis, and cost management. Our company uses a steering committee to supervise and evaluate data value and costs.	Mikalef, Boura, Lekakos, & Krogstie (2020)

Continued

	Our company has established data retention policies, such as the duration of the data life cycle.
	Our company has established routine procedures for data backup.
	Our company establishes and monitors data access rights, such as user access permissions.
	Our company classifies data according to its value.
	Our company monitors the alignment between data costs and data value.
	Our company provides training to business users and non-AI managers on data storage usage rules and costs.
	Our company has established communication mechanisms concerning the effectiveness of policy implementation and user needs.