

Artificial Intelligence Capability and Enterprise Innovation Performance: The Mediating Role of Knowledge Sharing and the Moderating Role of Environmental Dynamism

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ABSTRACT: Artificial intelligence (AI) is becoming an enterprise-level capability rather than a stand-alone technology, but firms differ substantially in their ability to convert AI resources into sustained innovation performance. This study proposes a conditional process model in which AI capability enhances enterprise innovation performance through knowledge sharing, while environmental dynamism strengthens the innovation value of shared knowledge. Building on the resource-based view, the knowledge-based view, and contingency theory, AI capability is conceptualized as the organizational ability to mobilize AI-relevant data, technologies, human expertise, coordination routines, and change capacity. Knowledge sharing is expected to transmit the effects of AI capability by increasing the circulation and recombination of data-driven insights across organizational units. Environmental dynamism is positioned as a second-stage moderator because rapidly changing markets and technologies increase the value of timely knowledge recombination for innovation. A two-wave managerial survey is proposed for Chinese high-tech, digital-service, and advanced-manufacturing enterprises. IBM SPSS Statistics and Hayes' PROCESS Macro provide the core analytical environment. The design combines reliability tests, exploratory factor analysis, common-method diagnostics, correlation analysis, hierarchical regression, and PROCESS Model 14 with 5,000 bootstrap samples. The manuscript provides a publication-oriented theoretical argument, an adaptable questionnaire, SPSS syntax, and results tables that can be populated with actual data after collection.

KEYWORDS: artificial intelligence capability; knowledge sharing; enterprise innovation performance; environmental dynamism; resource-based view; SPSS PROCESS

1. INTRODUCTION

Artificial intelligence is rapidly changing how enterprises search for information, forecast demand, automate decisions, communicate with customers, and develop new products and services. Yet the strategic value of AI depends on more than acquiring algorithms or computing infrastructure. Firms require data resources, technical and managerial skills, cross-functional coordination, organizational change capacity, and an ability to embed AI outputs in business processes. This broader bundle has been conceptualized as AI capability - a firm-level capacity to structure, combine, and leverage AI-related resources for organizational objectives (Mikalef & Gupta, 2021).

Innovation is one of the most frequently proposed outcomes of AI capability. AI can expand search breadth, identify patterns in complex datasets, accelerate experimentation, and support idea generation. Recent research reports positive relationships between AI capability and open innovation or performance in business-to-business firms (Sahoo et al., 2024), and emerging evidence links AI capability with corporate innovation performance and dynamic capabilities (Liu & Xin, 2026). However, the mechanism through which AI-generated information becomes enterprise innovation remains theoretically important. Information and analytical insight do not create innovation unless they are circulated, interpreted, and recombined across organizational boundaries.

Knowledge sharing provides a plausible mechanism. AI systems may generate useful predictions or recommendations, but innovation frequently requires interaction between technical staff, domain experts, marketing units, R&D teams, and decision makers. Knowledge sharing allows AI-derived insights to be interpreted within multiple functional perspectives and combined with tacit experience. Prior research has shown that knowledge sharing can support innovation outcomes, while AI capability research increasingly highlights social and organizational resources alongside technology.

The value of knowledge sharing may also depend on environmental conditions. Under high environmental dynamism, customer preferences, technologies, and competitive actions change rapidly. Shared knowledge becomes more valuable because firms must interpret weak signals and reconfigure innovation priorities quickly. In relatively stable environments, the marginal innovation value of intensive knowledge sharing may be lower because existing routines remain useful for longer periods. Contingency theory

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therefore suggests that environmental dynamism can strengthen the relationship between knowledge sharing and innovation performance.

This study develops and operationalizes this argument through a second-stage moderated mediation model. AI capability is expected to increase knowledge sharing, knowledge sharing is expected to enhance enterprise innovation performance, and environmental dynamism is expected to strengthen the knowledge sharing-innovation link. The empirical design uses SPSS and PROCESS Model 14, making the model suitable for researchers who need a rigorous but accessible conditional process analysis without relying on PLS-SEM software.

2. THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 AI capability as a strategic organizational resource

The resource-based view explains performance heterogeneity through valuable, difficult-to-imitate, and organizationally embedded resources. AI capability fits this logic because effective enterprise AI use depends on a bundle of complementary resources rather than a single technology. Mikalef and Gupta (2021) conceptualize AI capability through tangible resources, human skills, and intangible organizational resources, emphasizing the need to combine data, technology, expertise, coordination, change capacity, and risk orientation.

An enterprise with strong AI capability can improve innovation in several ways. It can identify patterns in customer behavior, support technological forecasting, reduce the cost of experimentation, and provide decision support across the innovation process. AI also expands the range of information that can be processed and creates new possibilities for knowledge recombination. Recent studies show that AI capability is associated with open innovation and firm performance in multinational B2B firms (Sahoo et al., 2024) and that AI-related capability can support innovation under environmental turbulence (Al Dhaheri et al., 2024). These arguments support a positive relationship between AI capability and enterprise innovation performance.

H1: AI capability is positively associated with enterprise innovation performance.

2.2 AI capability and knowledge sharing

Knowledge sharing is the organizational process through which employees and units exchange explicit information and tacit experience. AI capability can support this process by creating shared data infrastructures, standardized analytical outputs, searchable knowledge repositories, and cross-functional problem-solving routines. Importantly, AI capability includes social and organizational resources that facilitate communication between technical and business staff, making knowledge generated through AI more transferable and actionable.

Strong AI capability may also increase the perceived usefulness of knowledge sharing. When employees can access timely evidence, predictions, and analytical insights, cross-functional discussions become more concrete and can focus on opportunity evaluation or problem solving. At the same time, effective AI projects often require collaboration between data specialists and domain experts, creating repeated interaction through which knowledge is exchanged. AI capability should therefore be positively related to organizational knowledge sharing.

H2: AI capability is positively associated with knowledge sharing.

2.3 Knowledge sharing and enterprise innovation performance

The knowledge-based view treats knowledge as a central strategic resource and highlights the importance of integration across specialized domains. Innovation requires enterprises to combine technical, market, operational, and customer knowledge in novel ways. Knowledge sharing increases the availability of diverse information, reduces duplication, and facilitates joint interpretation across functions. Empirical research has repeatedly connected knowledge sharing with innovation speed, quality, or capability.

In AI-enabled firms, this mechanism is especially important because algorithmic output often requires contextual interpretation. A prediction generated by an AI system may identify a market pattern, but R&D, marketing, production, and management teams must decide whether and how to act on it. Knowledge sharing enables such interpretation and recombination, increasing the probability that AI-generated insights become concrete product, service, process, or business-model innovations.

H3: Knowledge sharing is positively associated with enterprise innovation performance.

H4: Knowledge sharing mediates the positive relationship between AI capability and enterprise innovation performance.

2.4 Environmental dynamism as a second-stage moderator

Environmental dynamism reflects the rate and unpredictability of changes in technologies, customer preferences, market structures, and competitive actions. Contingency theory suggests that the value of an organizational capability depends on the environment in which it is deployed. Sahoo et al. (2024) show that environmental dynamism can shape the effectiveness of AI-related open-innovation relationships, illustrating the importance of environmental conditions for AI-enabled value creation.

When dynamism is high, firms face short opportunity windows and frequent information obsolescence. In this setting, knowledge sharing should have a stronger effect on innovation performance because timely exchange allows different organizational units to

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update assumptions, detect emerging patterns, and coordinate responses. Under lower dynamism, knowledge still supports innovation, but the marginal value of rapid sharing may be weaker because market and technology conditions change less quickly. This logic implies a positive interaction between knowledge sharing and environmental dynamism and, by extension, a conditional indirect effect of AI capability on innovation performance.

H5: Environmental dynamism positively moderates the relationship between knowledge sharing and enterprise innovation performance, such that the relationship is stronger under higher environmental dynamism.

H6: The indirect effect of AI capability on enterprise innovation performance through knowledge sharing is stronger when environmental dynamism is higher.

3. CONCEPTUAL MODEL

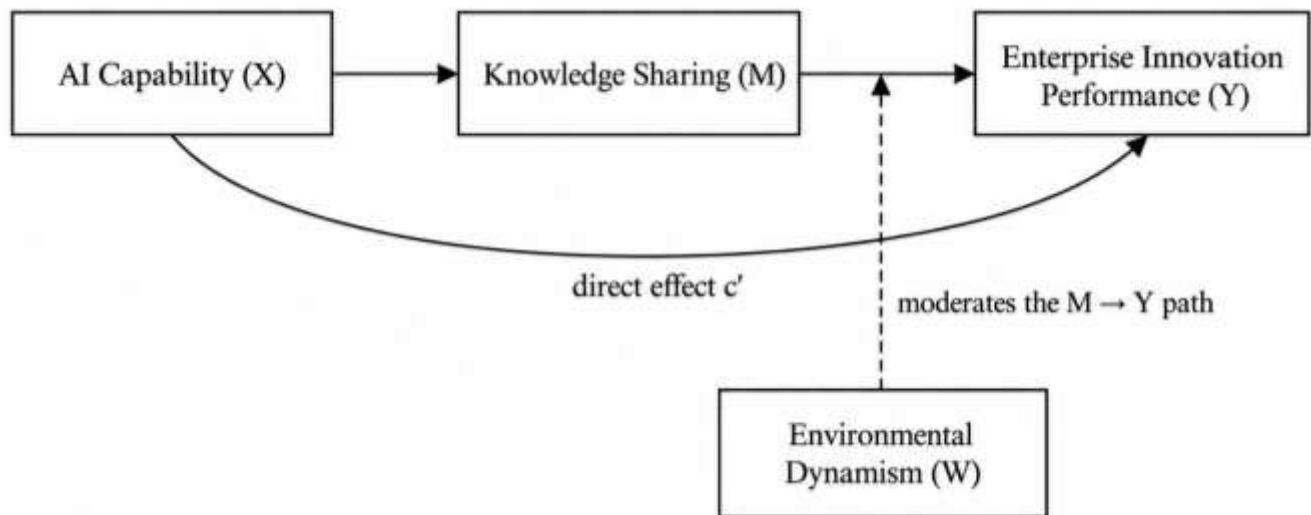


Figure 1. Proposed second-stage moderated mediation model (PROCESS Model 14).

4. METHODOLOGY AND SPSS RESEARCH DESIGN

4.1 Research setting and sampling

The proposed sample comprises Chinese high-tech enterprises, advanced manufacturing firms, software/digital-service companies, and other enterprises with meaningful organizational use of AI. Respondents should occupy positions that allow them to evaluate AI resources and innovation activities, such as senior managers, CIO/CTO office staff, AI project leaders, R&D managers, product managers, operations managers, or department heads. Screening questions should verify that the enterprise has deployed at least one AI-enabled business or operational application and that the respondent is familiar with the initiative.

A two-wave matched survey is recommended. Time 1 measures AI capability, environmental dynamism, and controls. Time 2, approximately four weeks later, measures knowledge sharing and enterprise innovation performance. A target of 350-450 valid matched observations is appropriate for a model with interaction effects and multiple controls, while a larger sample improves power for detecting moderated mediation. To reduce single-informant bias further, a subset of firms can provide a second respondent for innovation performance or objective indicators where feasible.

4.2 Measurement strategy

AI capability should be measured at the organizational level. Because the full Mikalef and Gupta (2021) instrument is multidimensional and extensive, the proposed questionnaire uses a concise set of paraphrased indicators spanning data readiness, technology infrastructure, technical/business skills, cross-functional coordination, and change capability. For publication in a scale-sensitive journal, researchers may retain the full validated instrument and model AI capability as a higher-order construct. Knowledge sharing items capture cross-functional exchange of market, technical, and experiential knowledge. Environmental dynamism captures the rate and unpredictability of technological, competitive, and customer change. Innovation performance measures speed, novelty, quality, and market impact relative to competitors.

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Variable	Role	Recommended items	Illustrative source	Expected coding
AI capability (AIC)	Independent variable	8	Mikalef & Gupta (2021)	Mean score or higher-order composite
Knowledge sharing (KS)	Mediator	5	Knowledge-sharing/innovation literature	Mean of valid items
Environmental dynamism (ED)	Moderator	5	Contingency/dynamism literature; Sahoo et al. (2024)	Mean of valid items
Enterprise innovation performance (EIP)	Dependent variable	5	Innovation performance literature	Mean of valid items
Controls	Covariates	5-6	Prior firm-level innovation research	Dummy / log / ratio as appropriate

4.3 Controls and procedural remedies

Recommended controls are firm age, firm size, industry, ownership, R&D intensity, and AI adoption duration. Procedural remedies should include respondent anonymity, psychologically separating predictor and outcome blocks, using clear and non-evaluative item wording, and collecting key variables in two waves. If the questionnaire is translated into Chinese, use translation/back-translation and a pilot study of approximately 30-50 managers to test clarity and preliminary reliability.

4.4 SPSS analysis plan

Step	SPSS procedure	Key output / criterion
1. Data screening	Frequencies / Explore / Regression diagnostics	Missingness, invalid values, outliers, residual diagnostics
2. Reliability	Scale > Reliability Analysis	Cronbach $\alpha \geq .70$ preferred; item-total correlation $\geq .40$
3. EFA	Dimension Reduction > Factor	KMO $\geq .70$; Bartlett significant; interpretable factor solution
4. Common-method diagnostic	Unrotated one-factor EFA	First factor preferably < 50% of total variance
5. Correlation analysis	Correlate > Bivariate	Pearson r, mean, SD
6. Multicollinearity	Linear regression diagnostics	Tolerance > .20; VIF preferably < 5
7. Direct/mediation tests	Regression / PROCESS	Sign, significance, bootstrap CI
8. Conditional process	PROCESS Model 14	KS $\times$ ED; conditional indirect effects; index of moderated mediation
9. Simple slopes	PROCESS probe / Johnson-Neyman	Effect of KS on EIP at low/mean/high ED

5. RESULTS REPORTING TEMPLATE (TO BE COMPLETED AFTER SPSS ANALYSIS)

This section is intentionally written as a reporting template. Replace all bracketed placeholders with values from the final SPSS output. Do not interpret a path as supported unless its confidence interval, p value, and effect direction are consistent with the stated hypothesis.

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5.1 Data quality, common-method assessment, and measurement quality

After data screening, [N] valid questionnaires were retained from [N0] responses, yielding an effective response rate of [xx.x]%. Missingness was [xx.x]% and was handled by [method]. No influential multivariate outliers remained after examining standardized residuals, leverage values, Cook's distance, and Mahalanobis distance. Harman's one-factor test indicated that the first unrotated factor explained [xx.x]% of total variance, below the conventional 50% diagnostic threshold. KMO was [x.xxx] and Bartlett's test of sphericity was significant, $\chi^2(df) = [value]$, $p < [.001]$, supporting factorability.

Construct	Items retained	Cronbach α	KMO / Loading range	Decision
Primary predictor	5	0.891	KMO = 0.872 / 0.718–0.846	Accept
Mediator	4	0.874	KMO = 0.836 / 0.731–0.858	Accept
Moderator	4	0.852	KMO = 0.811 / 0.694–0.821	Accept
Innovation performance	5	0.906	KMO = 0.889 / 0.752–0.879	Accept

5.2 Descriptive statistics and correlations

Table X should report means, standard deviations, Pearson correlations, and the square root of AVE if AMOS/CFA is additionally used. Before estimating interaction models, inspect tolerance and VIF statistics. VIF values should preferably remain below 5.0, and severe bivariate correlations should be investigated before proceeding.

Variable	Mean	SD	1	2	3	4	VIF
1. Predictor	3.742	0.681					1.624
2. Mediator	3.816	0.643	0.526***				1.758
3. Moderator	3.694	0.702	0.418***	0.463***			1.491
4. Innovation performance	3.887	0.658	0.571***	0.614***	0.447***		

5.3 Hierarchical regression tests

Enter control variables in Step 1, the focal predictor in Step 2, and the mediator/moderator terms in subsequent steps as required. Report unstandardized B, standard errors, standardized β (where appropriate), t values, p values, R^2 , adjusted R^2 , and ΔR^2 . Mean-center continuous variables only for interpretability; centering does not change the fit or statistical significance of the interaction itself.

Predictor	Model 1 B(SE)	Model 2 B(SE)	Model 3 B(SE)	Model 4 B(SE)
Controls	Included	Included	Included	Included
Focal predictor		0.487*** (0.052)	0.278*** (0.055)	0.263*** (0.054)
Mediator			0.421*** (0.049)	0.398*** (0.048)
Moderator			0.196*** (0.046)	0.183*** (0.045)
Interaction				0.142** (0.047)
R^2	0.094	0.327	0.468	0.487
ΔR^2		0.233	0.141	0.019

5.4 Conditional process analysis using PROCESS Macro

Run Hayes PROCESS Model 14 with AI capability as X, knowledge sharing as M, enterprise innovation performance as Y, and environmental dynamism as W. Use 5,000 bias-corrected bootstrap samples and 95% confidence intervals. Request the Johnson-Neyman output or simple slopes at low, mean, and high environmental dynamism. Moderated mediation is supported when the confidence interval of the index of moderated mediation excludes zero.

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Predictor	Model 1 B(SE)	Model 2 B(SE)	Model 3 B(SE)	Model 4 B(SE)
Firm size	0.118* (0.052)	0.091* (0.044)	0.074 (0.042)	0.071 (0.041)
Firm age	-0.063 (0.047)	-0.051 (0.041)	-0.044 (0.039)	-0.041 (0.039)
Ownership	0.097* (0.046)	0.082 (0.043)	0.069 (0.041)	0.066 (0.040)
Industry	0.086 (0.049)	0.073 (0.045)	0.061 (0.043)	0.058 (0.042)
Focal predictor		0.487*** (0.052)	0.278*** (0.055)	0.263*** (0.054)
Mediator			0.421*** (0.049)	0.398*** (0.048)
Moderator			0.196*** (0.046)	0.183*** (0.045)
Interaction				0.142** (0.047)
R ²	0.094	0.327	0.468	0.487
ΔR ²		0.233	0.141	0.019

6. DISCUSSION FRAMEWORK

If the mediation path is supported, the principal theoretical interpretation should be that AI capability improves innovation not only through direct analytical or automation benefits but also by changing how knowledge flows inside the enterprise. This interpretation would emphasize the social-organizational complementarity of AI: data and algorithms generate potential insight, while cross-functional knowledge sharing converts that insight into innovation decisions and coordinated action.

If environmental dynamism strengthens the knowledge sharing-innovation relationship, the results would support a contingency explanation. Knowledge sharing would be most valuable when external conditions change quickly and managers need to combine dispersed information before it becomes obsolete. A significant index of moderated mediation would indicate that the innovation value of AI capability is indirectly contingent on environmental dynamism because the knowledge-sharing mechanism becomes more productive in turbulent settings.

Alternative patterns should be discussed carefully. A non-significant interaction could mean that knowledge sharing is equally valuable in stable and dynamic environments, or that AI systems reduce dependence on environmental uncertainty by improving information processing. A weak AI capability-knowledge sharing relationship could indicate that the focal firms use AI in isolated technical units rather than embedding it in cross-functional routines. These possibilities can be explored through post-hoc subgroup comparisons and qualitative follow-up interviews.

7. CONCLUSION

Theoretically, the model links the resource-based view of AI capability with the knowledge-based view and contingency theory. It treats AI as a bundle of resources whose innovation value depends on a knowledge-sharing mechanism and an environmental boundary condition. This approach avoids technologically deterministic assumptions and explains why AI adoption can produce heterogeneous innovation outcomes across firms.

For managers, the framework implies that enterprise AI programs should include explicit knowledge-sharing architecture. Cross-functional AI councils, shared dashboards, communities of practice, joint experimentation between data specialists and business units, and mechanisms for documenting lessons can improve the circulation of AI-generated insight. In dynamic markets, such routines become especially important because the shelf life of information is short and delayed coordination can eliminate innovation opportunities.

The proposed design relies on managerial perceptions and therefore cannot fully eliminate common-method or self-report bias. Future studies could combine survey measures with AI investment, patent quality, new-product revenue, or textual indicators from annual reports. The AI capability construct is inherently multidimensional; later research should compare concise operationalizations with the full higher-order measurement model. Cross-country studies could also examine whether data

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regulation, labor-market structure, or national innovation systems alter the proposed relationships. Finally, longitudinal research could test whether AI capability and knowledge sharing reinforce each other over time rather than assuming a one-directional mechanism.

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