 http://dx.doi.org/10.18623/rvd.v23.5758

HOW ORGANIZATIONAL FOUNDATIONS SHAPE CHINESE AI INNOVATION PERFORMANCE

COMO OS FUNDAMENTOS ORGANIZACIONAIS MOLDAM O DESEMPENHO DA INOVAÇÃO EM IA CHINESA

Article received on: 12/5/2025
Article accepted on: 3/4/2026

Yu Zhao*
***College of Innovation & Industrial Management, King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand
Orcid: https://orcid.org/0009-0009-6293-756
zhaoevan87@gmail.com

Paitoon Pimdee*
***School of Industrial Education and Technology, King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand
Orcid: https://orcid.org/0000-0002-3724-2885
paitoon.pi@kmitl.ac.th

Aukkapong Sukkamart*
***School of Industrial Education and Technology, King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand
Orcid: https://orcid.org/0000-0002-1234-4033
aukkapong.su@kmitl.ac.th

The authors declare that there is no conflict of interest

Abstract
Chinese AI firms do not just need to spend on technology. They also need to turn organizational resources into real innovation ability. We tested a model linking organizational learning (OL), knowledge management (KM), human capital (HC), and social capital (SC) to innovation capability (IC) and innovation performance (IP). Using survey data from 362 managers across China's three main AI clusters, we found that OL, KM, and HC boost IC — but SC does not. For IP, OL, HC, SC, and IC all help, while KM does not directly matter. The mediation story is nuanced: OL and HC work both directly and indirectly through IC; KM works only indirectly; SC works directly, bypassing IC entirely. Our findings suggest that in China's AI industry, innovation capability is a selective bridge, not a universal one.

Keywords: AI Firms. CB-SEM. China. Innovation Performance. Innovation Capability.

Resumo
As empresas chinesas de IA não precisam apenas investir em tecnologia. Elas também precisam transformar recursos organizacionais em verdadeira capacidade de inovação. Testamos um modelo que conecta aprendizado organizacional (AO), gestão do conhecimento (GC), capital humano (CH) e capital social (CS) à capacidade de inovação (CI) e ao desempenho da inovação (DI). Usando dados de survey com 362 gestores em três principais polos de IA da China, descobrimos que AO, GC e CH impulsionam a CI — mas CS não. Em relação ao DI, AO, CH, CS e CI todos ajudam, enquanto GC não tem efeito direto relevante. O quadro da mediação é matizado: AO e CH atuam tanto direta quanto indiretamente por meio da CI; GC atua apenas indiretamente; CS atua diretamente, contornando a CI por completo. Nossos achados sugerem que, na indústria chinesa de IA, a capacidade de inovação é uma ponte seletiva, não universal.

Palavras-chave: *Empresas de IA. CB-SEM. China. Desempenho da Inovação. Capacidade de Inovação.*

1 INTRODUCTION

China’s artificial intelligence (AI) industry has grown into a large innovation system that links foundation models, infrastructure, algorithm development, and industry applications. Firms in this system do not only adopt digital technologies. They also create new technical knowledge and commercial outputs (Cricchio *et al*., 2025). Nevertheless, innovation performance still differs across Chinese AI firms (Zhao *et al*., 2026). Even with strong policy support and high technology spending, some firms turn organizational resources into products, processes, and marketable solutions better than others (Wu *et al*., 2025).

Existing research explains only part of this variation. Recent studies show that AI innovation depends not only on technology adoption but also on how firms learn, share knowledge, manage talent, and use external ties (Liu & Li, 2025). Still, these factors are often studied individually. Innovation performance is also often treated as a direct result of investment rather than as the outcome of a wider organizational conversion process. Our earlier systematic review reached a similar conclusion. Organizational learning, knowledge management, human capital, social capital, and innovation capability are often discussed in the literature. However, they are rarely tested together in a single firm-level model of China's AI industry (Teece, 2007). The main question, therefore, is not whether organizational resources matter. It is how they relate to innovation performance in Chinese AI firms.

To address this gap, this study tests an integrated model. In this model, organizational learning (OL), knowledge management (KM), human capital (HC), and social capital (SC) are the main organizational foundations. Innovation capability (IC) is the key mechanism for building capability, and innovation performance (IP) is the outcome. The model draws on dynamic-capabilities reasoning. This view holds that resources create value only when firms turn them into stable innovation routines (Saunila, 2020). Using 362 validated firm-level responses from Chinese AI firms, the results showed that OL, KM, and HC were positively associated with IC, but SC was not. For IP, OL, HC, SC, and IC, significant positive associations were observed, whereas the direct association of KM was not significant. The mediation results also suggested complementary mediation for OL and HC, an indirect-only pattern for KM, and no significant indirect effect for SC.

These findings contribute in three ways. First, they bring together four organizational foundations into a single model of innovation performance in Chinese AI firms. Second, they extend dynamic-capabilities reasoning by showing that IC is a selective rather than universal transmission mechanism. Third, they show that internal organizational resources and external relational resources do not reach innovation performance through the same path. The article, therefore, asks how different organizational foundations relate to innovation capability and innovation performance in Chinese AI firms, and whether innovation capability acts as a common or differentiated transmission mechanism across these relationships.

2 LITERATURE REVIEW

2.1 Innovation capability and innovation performance (IP)

Innovation capability is the firm’s ability to turn knowledge, technology, and organizational resources into new products, processes, and solutions (Mendoza-Silva, 2021). In dynamic-capability terms, it is the mechanism that turns dispersed resources into performance-related outputs (Saunila, 2020). Related evidence also shows that digital technologies can support organizational performance through knowledge and innovation processes (Kiziloglu, 2015). In AI settings, firms with stronger innovation capability should be better able to commercialize new ideas steadily and efficiently. This suggests a positive association with innovation performance. Accordingly:

H1. Innovation capability is positively associated with innovation performance.

2.2 Organizational learning (OL)

Organizational learning reflects commitment to learning, shared vision, and openness to revising assumptions. Firms with stronger learning orientation are better able to absorb technical knowledge, share lessons across projects, and adjust routines as AI technologies and applications change. Prior work also links organizational learning with stronger firm innovation capability (Soomro *et al*., 2021). This suggests that organizational learning will be positively related to innovation capability and innovation performance (Gold *et al*., 2001). Accordingly:

H2. Organizational learning is positively associated with innovation capability.

H3. Organizational learning is positively associated with innovation performance.

2.3 Knowledge management (KM)

Innovation capability is the firm’s ability to turn knowledge, technology, and organizational resources into new products, processes,

Knowledge management (KM) captures a firm's ability to acquire, share, store, and apply knowledge systematically. A capabilities perspective also suggests that firms need suitable knowledge infrastructure and process capabilities to turn dispersed knowledge into effective action (Abbas *et al*., 2020). In AI firms, these routines reduce knowledge fragmentation, support cross-functional coordination, and make both codified and tacit knowledge easier to reuse in development work (Do *et al*., 2022). This suggests that KM will be positively related to innovation capability. It also relates to innovation performance by reducing duplication and improving the use of new knowledge in commercialization tasks. Prior evidence also indicates that knowledge management capacity can mediate the relationship between strategic human resource practices and innovation performance (Chen & Huang, 2009). Accordingly:

H4. Knowledge management is positively associated with innovation capability.

H5. Knowledge management is positively associated with innovation performance.

2.4 Human capital (HC)

Human capital refers to the knowledge, experience, and skills held by employees and managers (Al Frijat & Elamer, 2025). In AI firms, this resource is especially important because innovation depends on scarce technical expertise, managerial judgment, and the ability to align data, algorithms, products, and commercialization work.

This suggests that human capital will be positively related to innovation capability and innovation performance in AI firms. Accordingly:

H6. Human capital is positively associated with innovation capability.

H7. Human capital is positively associated with innovation performance.

2.5 Social capital (SC)

Social capital concerns the resources embedded in relationships, including network structure, trust, reciprocity, and shared understanding (Ganguly *et al*., 2019). In innovation settings, these relational assets can support capability building by making knowledge exchange and tacit learning easier. They may also relate more directly to innovation performance by giving firms access to complementary assets, information, and commercialization channels (Ahn & Kim, 2017). Prior evidence also shows that relational and cognitive dimensions of social capital can help firms turn employee knowledge into stronger innovation outcomes (Xinhua, 2026). Accordingly:

H8. Social capital is positively associated with innovation capability.

H9. Social capital is positively associated with innovation performance.

2.6 Mediating role of innovation capability (IC)

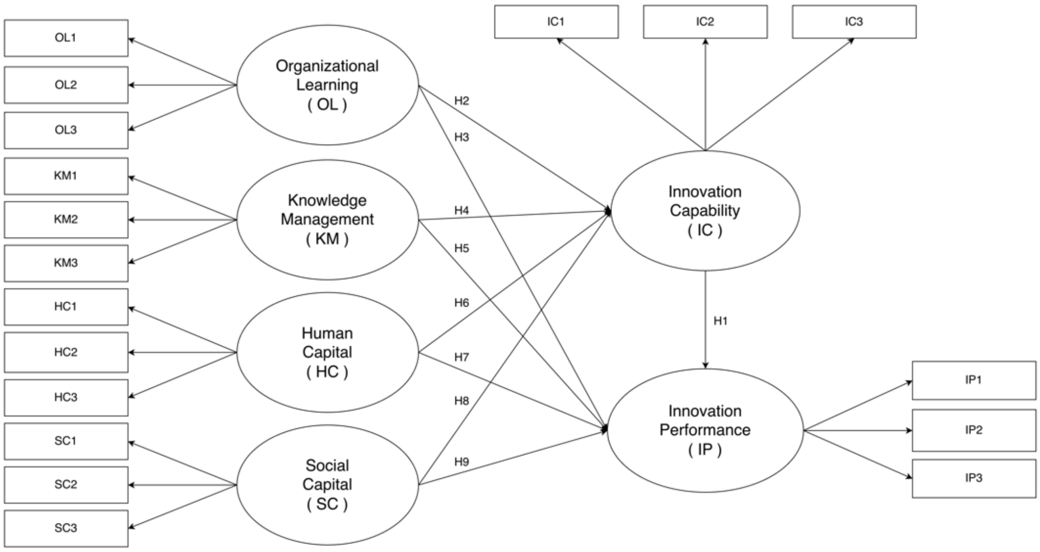
Dynamic-capability reasoning suggests that organizational resources create value when firms turn them into firm-specific capabilities. This implies that OL, KM, HC, and SC may affect IP indirectly through IC. The direct paths are retained because some effects may also operate through execution, coordination, and market access rather than solely through capability building. This setup is also consistent with prior review evidence from China’s AI-industry literature. The empirical analysis, therefore, tests the indirect effects of OL, KM, HC, and SC on IP via IC.

2.7. Proposed conceptual model

Figure 1 visualizes the study's proposed conceptual model.

Figure 1

Proposed conceptual model



3 METHODS

3.1 Research design and study context

This study used a quantitative, cross-sectional survey design. It examined the organizational foundations of innovation performance in Chinese AI firms. The model was derived from prior review-based synthesis and was used for firm-level hypothesis testing. The study focused on AI-related enterprises in Mainland China that develop, integrate, or commercialize AI technologies and application solutions. The sampling frame centered on the country's major AI clusters. These clusters contain a large share of Chinese AI enterprises and remain the core regional ecosystems for industrial AI innovation (Baharum *et al*., 2023; Yu *et al*., 2022).

The unit of analysis was the firm. The source of information was a managerial key informant. Eligible respondents included senior executives, R&D (research &

development) or technology managers, and human resource managers. These respondents were expected to have enough cross-functional knowledge of their firms' learning routines, knowledge practices, talent base, relational resources, innovation capability, and innovation outcomes. The single-respondent design was therefore treated as a key-informant approach rather than as a general employee survey.

3.2 Research design and study context

The model included six latent constructs, 18 observed dimensions, and 54 questionnaire items. The study therefore sought at least 360 valid firm-level responses. This target reflected the 18-dimensional measurement structure and the common expectation that covariance-based SEM (structural equation model) models of this complexity should be estimated with large samples, usually above 200 cases, and with sufficient observations for the model size.

The sampling strategy combined regional stratification with respondent screening. Firms were approached from the Yangtze River Delta, the Beijing–Tianjin–Hebei region, and the Guangdong-centered southern cluster. One eligible managerial respondent was invited from each enterprise. This helped preserve firm-level independence. To qualify for inclusion, the enterprise had to operate in an AI-related business in Mainland China, and the respondent had to hold a managerial role with relevant knowledge of the focal organizational processes and innovation outcomes.

3.3 Instrument development and measurement structure

The questionnaire had two sections. The first section captured respondent and firm characteristics, including age, gender, position, education, work experience, year of firm founding, and regional location. The second section measured the six latent constructs with a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). All construct measures were adapted from established studies and refined to yield firm-level responses from managerial respondents in Chinese AI enterprises.

In total, the instrument contained 54 items grouped into 18 observed dimensions. Each focal construct was modeled as a second-order reflective construct with three first-order dimensions. This specification was used because the dimensions were treated as manifestations of broader organizational attributes rather than formative components. It was also consistent with the structure of the adapted source scales and supported parsimonious structural estimation.

3.4 Content validity and pilot assessment

Before pilot testing, the draft questionnaire underwent expert review (Damkhong *et al*., 2025; Prasopkittikun *et al*., 2020). The review focused on content coverage, clarity of wording, and fit with the Chinese AI-firm context. The panel comprised five members. These included four university professors with expertise in innovation, management, and information systems, as well as one senior executive from a Chinese AI-related enterprise. Based on their feedback, several items were refined before the pilot survey to improve construct representation and contextual fit.

The pilot survey was then conducted through Wenjuanxing. A total of 180 questionnaires were distributed, and 165 valid responses were retained, yielding an effective response rate of 91.67%. Although the pilot sample was relatively large, it was used only for wording refinement and reliability screening. It was not pooled with the main survey for hypothesis testing. Because the adapted scales were theory-driven and derived from established measures, the pilot stage focused on clarity of wording and reliability screening rather than exploratory re-specification of the factor structure.

The pilot analysis, therefore, focused on feasibility, corrected item–total correlations (CITC), and internal consistency reliability rather than full SEM estimation (Damkhong *et al*., 2025; Prasopkittikun *et al*., 2020). Cronbach's alpha values of 0.70 or higher were treated as acceptable. The pilot results showed satisfactory internal consistency across all six constructs Table 1), with construct-level alpha values ranging from 0.800 to 0.847 and CITC values ranging from 0.529 to 0.748. These results supported retention of all items in the main survey.

Table 1

Pilot reliability and item diagnostics

Construct	Items	Cronbach's α	CITC range
Organizational Learning (OL)	9	0.800	0.607–0.719
Knowledge Management (KM)	9	0.826	0.533–0.707
Human Capital (HC)	9	0.839	0.591–0.748
Social Capital (SC)	9	0.847	0.564–0.705
Innovation Capability (IC)	9	0.812	0.533–0.610
Innovation Performance (IP)	9	0.831	0.529–0.645

3.5 Data collection procedure and common method precautions

The main survey was administered online through Wenjuanxing to qualified managerial respondents from Chinese AI firms (Kock *et al*., 2021). At the start of the questionnaire, respondents were informed of the study purpose, the academic use of the data, the voluntary nature of participation, and the confidentiality of their responses. Participation began only after informed consent had been obtained. Screening items were used to verify that the respondent worked in an AI-related enterprise in Mainland China, held an eligible managerial role, and belonged to the intended sampling frame. The survey was distributed through targeted managerial and enterprise networks within the selected AI clusters rather than through open public circulation. This helped maintain respondent eligibility and contributed to the high proportion of usable responses.

Several procedural steps were used to reduce the risk of common method bias (Podsakoff *et al*., 2003). First, the study relied on knowledgeable managerial informants rather than general employees. Second, the questionnaire used construct blocks adapted from validated scales and refined through scholarly review, expert evaluation, and pilot feedback. Third, the survey introduction emphasized anonymity and stated that there were no right or wrong answers. This helped reduce evaluation apprehension and socially desirable responding Demir & Tortop, 2026). During data cleaning, cases with substantial missingness, duplicate submissions, obvious straight-lining or careless response patterns, ineligible respondents, or non-AI firms were removed before formal analysis. The formal analysis also included a Harman single-factor test as a post hoc diagnostic.

3.6 Data analysis strategy

The empirical analysis was conducted using IBM SPSS Statistics (version 26) for data screening, descriptive statistics, and a preliminary reliability assessment, followed by IBM SPSS AMOS (version 26) for covariance-based structural equation modeling (CB-SEM). CB-SEM with maximum likelihood estimation (MLE) was chosen because: (a) the study tests a confirmatory, theory-driven model rather than an exploratory or predictive one; (b) all measurement scales were adapted from established instruments with known psychometric properties; and (c) preliminary tests confirmed that the data did not severely violate multivariate normality (skewness ranged from –0.198 to 0.279; kurtosis from –1.141 to –1.056), satisfying the assumptions for MLE (Ampa *et al*., 2026; Collier, 2020).

The analysis followed seven stages.

1) First, item data screening and cleaning to identify missing values, duplicate cases, outliers, and invalid responses before formal analysis;
2) Descriptive statistics to summarize the respondent profile, firm characteristics, and the general distribution of the observed variables;
3) Reliability and convergent validity assessment using Cronbach's alpha, composite reliability (CR), standardized factor loadings (λ), and average variance extracted (AVE) (Quintero-Sepúlveda *et al*., 2025);
4) Discriminant validity assessment using the Fornell–Larcker criterion together with competing second-order CFA models that compare the six-factor benchmark with progressively merged alternatives;
5) Confirmatory factor analysis (CFA) and measurement-model fit evaluation using χ^2/df, Normed Fit Index (NFI), root mean square residual (RMR), incremental fit index (IFI), Tucker–Lewis index (TLI), comparative fit index (CFI), and root mean square error of approximation (RMSEA) (Siriphatcharachot *et al*., 2025);
6) Structural model analysis to estimate the nine hypothesized direct effects and the R^2 values of the endogenous constructs, especially IC and IP;

7) Mediation analysis to test the indirect effects of OL, KM, HC, and SC on IP through IC using bias-corrected bootstrap confidence intervals with 5,000 resamples (Lieophairot *et al*., 2025).

IBM SPSS Statistics was used for data screening, descriptive statistics, and the preliminary assessment of reliability and convergent validity. IBM SPSS AMOS was used for CFA, measurement-model fit evaluation, structural model estimation, and mediation testing. Discriminant validity was assessed using the Fornell–Larcker criterion and supplementary competing second-order CFA models (Charoentham *et al*., 2025) that progressively merged constructs from left to right in the following order: OL, KM, HC, SC, IC, and IP. Any model re-specification remained theory-driven and was reported transparently rather than justified only by statistical improvement.

4 RESULTS

4.1 Descriptive patterns

Mean scores ranged from 2.86 (IC) to 3.29 (OL). All inter-construct correlations were positive and significant ($p < 0.01$), with the strongest between IC and IP ($r = 0.574$) and the weakest between KM and HC ($r = 0.248$). Skewness and kurtosis were within acceptable limits.

4.2 Measurement model

Reliability and convergent validity were good. Cronbach's alpha ranged from 0.842 to 0.870, composite reliability from 0.762 to 0.877, and average variance extracted (AVE) from 0.518 to 0.705. Standardized loadings ranged from 0.646 to 0.926. Discriminant validity was supported: for each construct, the square root of AVE exceeded its correlations with other constructs (Fornell-Larcker criterion). The six-factor second-order CFA model fit well: $\chi^2/df = 1.178$, CFI = 0.973, TLI = 0.971, RMSEA = 0.022. This model outperformed all merged alternatives (e.g., five-factor, one-factor), confirming that the six constructs are distinct. Table 2 presents a compact validity summary, including Cronbach’s alpha, composite reliability (CR), average variance extracted (AVE), and the full latent correlation matrix with the square root of AVE on the diagonal (bolded).

Table 2

Reliability, convergent validity, and discriminant validity (Fornell-Larcker criterion)

Reliability, convergent validity, and discriminant validity (Fornell-Larcker criterion)

Construct	α	CR	AVE	OL	KM	HC	SC	IC	IP
OL	0.842	0.762	0.518	**0.720**					
KM	0.860	0.783	0.546	0.378	**0.739**				
HC	0.857	0.766	0.522	0.545	0.346	**0.722**			
SC	0.848	0.772	0.531	0.530	0.421	0.571	**0.729**		
IC	0.842	0.815	0.598	0.626	0.541	0.618	0.512	**0.773**	
IP	0.870	0.877	0.705	0.701	0.451	0.683	0.641	0.734	**0.840**

Notes: α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. Bolded diagonal values are the square root of AVE. Off-diagonal values are latent construct correlations (from the second-order CFA). All correlations are significant at $p < 0.001$.

4.3 Structural model

We tested the nine direct hypotheses. The model explained 57.6% of the variance in IC and 70.9% in IP. Table 3 shows the standardized paths.

Table 3

Hypothesis testing results

Hypothesis	Path	Std. β	p	Supported?
H1	IC → IP	0.317	0.002	Yes
H2	OL → IC	0.321	<0.001	Yes
H3	OL → IP	0.270	0.002	Yes
H4	KM → IC	0.294	<0.001	Yes
H5	KM → IP	0.015	0.820	No
H6	HC → IC	0.323	<0.001	Yes
H7	HC → IP	0.219	0.012	Yes
H8	SC → IC	0.033	0.717	No
H9	SC → IP	0.204	0.010	Yes

Note: β = standardized coefficient. IC = innovation capability, IP = innovation performance, OL = organizational learning, KM = knowledge management, HC = human capital, SC = social capital.

4.4 Mediation analysis

We used bootstrapping (5,000 samples) to test indirect effects through IC.

OL: Total effect on IP = 0.371 ($p < 0.001$). Direct effect = 0.270 ($p = 0.012$). Indirect effect = 0.102 (95% CI [0.020, 0.224]). This is **complementary mediation** — OL helps IP both directly and by building IC.

KM: Total effect = 0.108 ($p = 0.110$, not significant). Direct effect = 0.015 ($p = 0.857$). Indirect effect = 0.093 (95% CI [0.021, 0.203]). **Indirect-only mediation** — KM only matters when it first boosts IC.

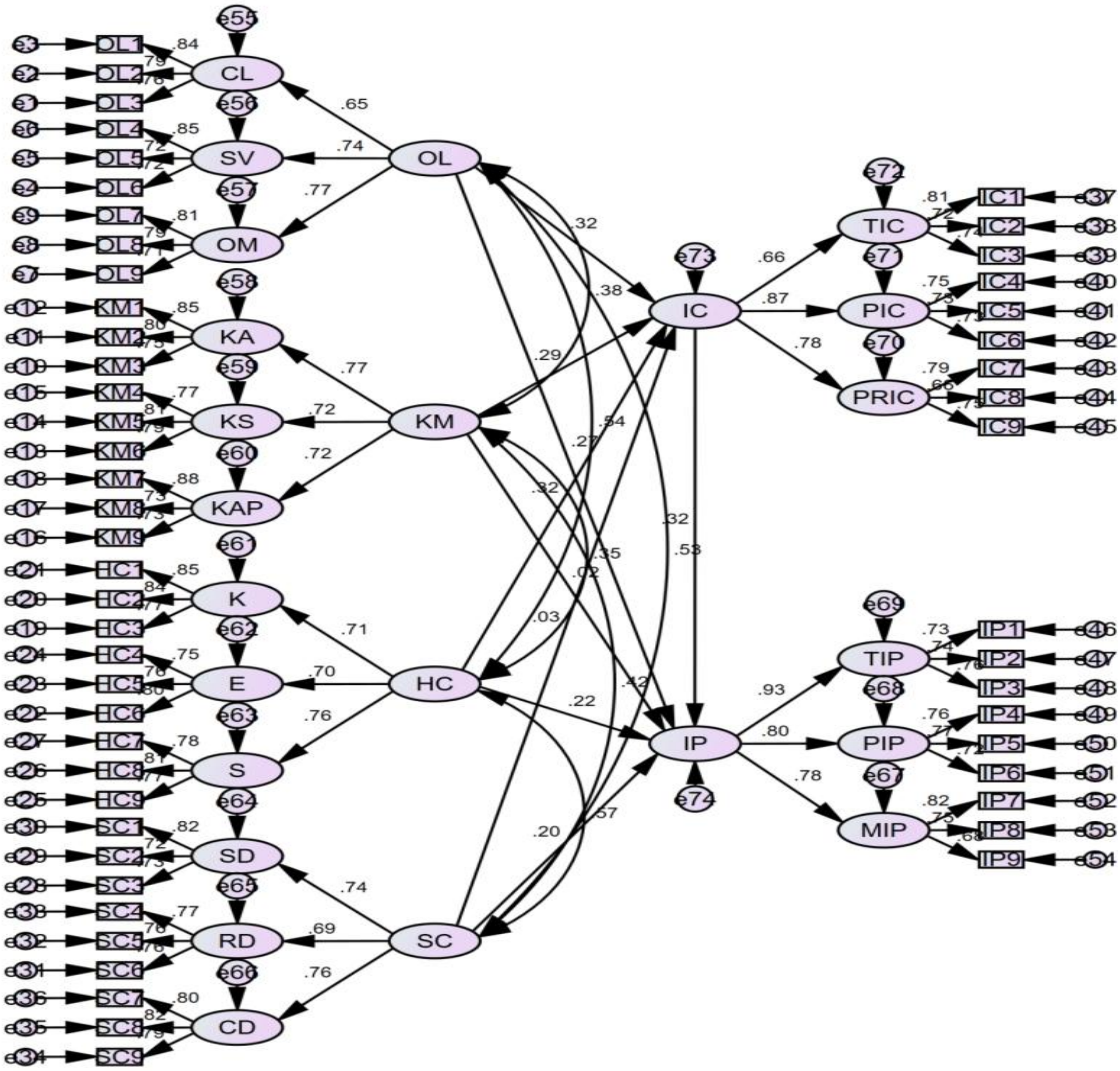
HC: Total effect = 0.321 ($p = 0.001$). Direct = 0.219 ($p = 0.026$). Indirect = 0.102 (95% CI [0.022, 0.226]). Again, **complementary mediation**.

SC: Total effect = 0.215 ($p = 0.023$). Direct = 0.204 ($p = 0.018$). Indirect = 0.011 (95% CI [-0.068, 0.087]). **No significant indirect effect** — SC works directly on IP, without needing IC.

Figure 2 shows the final structural model with standardized coefficients (identical to the original, but with only this figure).

Figure 2

Final structural model with standardized coefficients



5 DISCUSSION

Our results tell a clear story. Three internal organizational foundations — learning, knowledge management, and human capital — all help build innovation capability. Social capital does not. That is our first key finding. In Chinese AI firms, external relationships seem to serve access and coordination, rather than deep internal capability-building. This differs from some earlier studies but fits the fast-moving, cluster-based ecosystem, where firms often rely on government platforms and industry associations.

Second, for innovation performance, the pathways are split. Learning, human capital, social capital, and innovation capability all have direct positive links. However, knowledge management alone has no direct effect — it must first be converted into capability. That is a practical warning: building a knowledge repository or sharing system does not automatically improve performance unless the firm can turn that knowledge into usable innovation routines.

Third, the mediation patterns refine the picture. Learning and human capital work through two channels — direct and via capability. Knowledge management works only through capability. Social capital bypasses capability entirely. This extends dynamic capabilities theory: the resource-capability-performance chain is not the same across all types of resources. Relational resources may speed up market access, pilot projects, or regulatory approval without ever becoming a stable internal innovation routine.

These findings matter for managers. If you are a Chinese AI executive, invest in learning systems and talent — they pay off twice. Treat knowledge management as a capability-building tool, not a quick fix (Promsiri, 2025). Moreover, do not ignore social capital; it directly improves performance, just not through the innovation capability route you might expect.

6 CONCLUSIONS

We tested whether OL, KM, HC, and SC predict innovation performance in Chinese AI firms and whether IC mediates those effects. Using 362 manager responses and CB-SEM, we found that OL, KM, and HC boost IC, but SC does not. For IP, OL, HC, SC, and IC all help directly; KM does not. Mediation shows complementary patterns for OL and HC, an indirect-effect only for KM, and no indirect effect for SC. Innovation capability is a selective transmission mechanism, not a universal one.

7 PRACTICAL IMPLICATIONS

For managers in Chinese AI firms, our findings suggest three actionable steps. First, invest in organizational learning and human capital—they improve innovation performance through two channels (direct and capability-mediated). Second, treat knowledge management as a capability-building tool, not a standalone performance driver. Building a knowledge repository is useful only if it feeds into innovation routines. Third, maintain external social ties even if they do not deepen internal capability; social capital directly accelerates performance through faster market access, partnerships, and legitimacy. Policymakers should support cluster-level platforms that facilitate both capability-building (training, knowledge sharing) and direct commercialization (pilot projects, regulatory sandboxes).

8 LIMITATIONS AND FUTURE DIRECTIONS

This study is cross-sectional, so causality remains a claim, not a proof—single informants per firm risk bias, even with procedural controls. Our sample covers China's top three AI clusters, so generalizing to smaller regions requires caution. We used perceptual performance measures; future work could add patent data or new product revenue. Future research could use paired surveys (manager + engineer) or objective patent data to reduce same-source bias. Finally, the direct effect of SC on IP without IC mediation needs exploration — what exactly does social capital deliver? Faster partnerships? Legitimacy? That is a good next question.

REFERENCES

Abbas, J., Zhang, Q., Hussain, I., Akram, S., Afaq, A., & Shad, M. A. (2020). Sustainable innovation in small medium enterprises: The impact of knowledge management on organizational innovation through a mediation analysis by using SEM approach. *Sustainability*, *12*(6), 2407. https://doi.org/10.3390/su12062407

Ahn, S.-Y., & Kim, S.-H. (2017). What makes firms innovative? The role of social capital in corporate innovation. *Sustainability*, *9*(9), 1564. https://doi.org/10.3390/su9091564

Al Frijat, Y. S., & Elamer, A. A. (2025). Human capital efficiency, corporate sustainability, and performance: Evidence from emerging economies. *Corporate Social Responsibility and Environmental Management*, *32*(2), 1457–1472. https://doi.org/10.1002/csr.3013

Ampa, A. T., Rijal, S., Tadampali, A. C. T., Nurwahida, N., & Purnamasari, W. (2026). Entrepreneurial mindset of Generation Z: The role of self-efficacy and achievement motivation in entrepreneurship education. *Jurnal Pendidikan Progressif*, *16*, 367–383. https://doi.org/10.23960/jpp.v16i1.pp367-383

Baharum, H., Ismail, A., Awang, Z., McKenna, L., Ibrahim, R., Mohamed, Z., & Hassan, N. H. (2023). The study adapted instruments based on confirmatory factor analysis (CFA) to validate measurement models of latent constructs. *International Journal of Environmental Research and Public Health*, *20*(4), 2860. https://doi.org/10.3390/ijerph20042860

Charoentham, M., Kantathanawat, T., Pimdee, P., & Apisuksakul, K. (2025). Enhancing teaching and supervisory staff's creative problem-solving skills. *Emerging Science Journal*, *9*(Special Issue), 112–133. http://dx.doi.org/10.28991/ESJ-2025-SIED1-07

Chen, C.-J., & Huang, J.-W. (2009). Strategic human resource practices and innovation performance: The mediating role of knowledge management capacity. *Journal of Business Research*, *62*(1), 104–114. https://doi.org/10.1016/j.jbusres.2007.11.016

Collier, J. E. (2020). *Applied structural equation modeling using AMOS: Basic to advanced techniques*. Routledge. https://doi.org/10.4324/9781003018414

Cricchio, J., Barabuffi, S., Crupi, A., & Di Minin, A. (2025). China's new knowledge brokers: A patent citations network analysis of the artificial intelligence open innovation ecosystem. *Journal of Engineering and Technology Management*, *76*, 101870. https://doi.org/10.1016/j.jengtecman.2025.101870

Damkhong, S., Akkarasuwannakul, A., Raksanam, B., Tubthieng, W., & Raham, P. (2025). Community readiness for an aging society in semi-rural and rural communities of Trang Province, Southern Thailand: A mixed-methods approach. *Journal of Cultural Analysis and Social Change*, *10*(3), 303–315. https://doi.org/10.64753/jcasc.v10i3.2413

Demir, B., & Tortop, H. S. (2026). Development of the techno-mathematical literacy scale (TmLS): A validity and reliability study. *Journal of Mathematics Education and Teaching Practice*, Advanced Online Publication, 1–12. https://izlik.org/JA76AF39XX

Do, H., Budhwar, P., Shipton, H., Nguyen, H.-D., & Nguyen, B. (2022). Building organizational resilience, innovation through resource-based management initiatives, organizational learning, and environmental dynamism. *Journal of Business Research*, *141*, 808–821. https://doi.org/10.1016/j.jbusres.2021.11.090

Ganguly, A., Talukdar, A., & Chatterjee, D. (2019). Evaluating the role of social capital, tacit knowledge sharing, knowledge quality, and reciprocity in determining innovation capability of an organization. *Journal of Knowledge Management*, *23*(6), 1105–1135. https://doi.org/10.1108/JKM-03-2018-0190

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. *Journal of Management Information Systems*, *18*(1), 185–214. https://doi.org/10.1080/07421222.2001.11045669

Kiziloglu, M. (2015). The effect of organizational learning on firm innovation capability: An investigation in the banking sector. *Global Business and Management Research*, *7*(3), 17–33.

Kock, F., Berbekova, A., & Assaf, A. G. (2021). Understanding and managing the threat of common method bias: Detection, prevention, and control. *Tourism Management*, *86*, 104330. https://doi.org/10.1016/j.tourman.2021.104330

Lieophairot, R., Rojniruttikul, N., & Chaveesuk, S. (2025). Factors influencing rail service passenger loyalty among older Thai adults. *Sustainability*, *17*(18), 8240. https://doi.org/10.3390/su17188240

Liu, L. Q., & Li, C. Y. (2025). How does applying artificial intelligence influence firms' ambidextrous innovation performance? Evidence obtained from Chinese A-share listed firms. *Sustainability*, *17*(23), 10430. https://doi.org/10.3390/su172310430

Mendoza-Silva, A. (2021). Innovation capability: A systematic literature review. *European Journal of Innovation Management*, *24*(3), 707–734. https://doi.org/10.1108/EJIM-09-2019-0263

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Prasopkittikun, T., Srichantaranit, A., & Chunyasing, S. (2020). Thai nurses' perceptions and practices of family-centered care: The implementation gap. *International Journal of Nursing Sciences*, *7*(1), 74–80. https://doi.org/10.1016/j.ijnss.2019.09.013

Promsiri, T. (2025). AI and the psychology of educational disruption: Historical patterns and cognitive implications. *Acta Psychologica*, *260*, Article 105637. https://doi.org/10.1016/j.actpsy.2025.105637

Quintero-Sepúlveda, I. C., Restrepo-Salazar, E. F., Hernández-Arias, B. E., & Salazar-Valencia, P. A. (2025). Innovation skills in Colombian university students. *Industry and Higher Education*. Advance online publication. https://doi.org/10.1177/09504222251388166

Saunila, M. (2020). Innovation capability in SMEs: A systematic review of the literature. *Journal of Innovation & Knowledge*, *5*, 260–265. https://doi.org/10.1016/j.jik.2019.11.002

Siriphatcharachot, P., Sukkamart, A., Thongkaw, A., Pimdee, P., & Moto, S. (2025). High school student creativity, innovation, and teamwork skills from teacher's perspective: A second-order confirmatory factor analysis. *International Journal of Instruction*, *18*(1), 39–60. https://e-iji.net/ats/index.php/pub/article/view/682

Soomro, B. A., Mangi, S., & Shah, N. (2021). Strategic factors and significance of organizational innovation and organizational learning in organizational performance. *European Journal of Innovation Management*, *24*(2), 481–506. https://doi.org/10.1108/EJIM-05-2019-0114

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Wu, Q. Q., Qalati, S. A., Tajeddini, K., & Wang, H. J. (2025). The impact of artificial intelligence adoption on Chinese manufacturing enterprises' innovativeness: New insights from a labor structure perspective. *Industrial Management & Data Systems*, *125*(3), 849–874. https://doi.org/10.1108/IMDS-06-2023-0378

Xinhua. (2025, December 15). China's core AI industry to top 1.2 trillion yuan in 2025. *Xinhua Net*. http://english.scio.gov.cn/chinavoices/2025-12/15/content_118227982.html

Yu, Z., Liang, Z., & Xue, L. (2022). A data-driven global innovation system approach and the rise of China's artificial intelligence industry. *Regional Studies*, *56*(4), 619–629. https://doi.org/10.1080/00343404.2021.1954610

Zhao, Y., Pimdee, P., & Sukkamart, A. (2026). Influencing factors of firm-level innovation performance in China's artificial intelligence industry: A systematic review. *Edelweiss Applied Science and Technology*, *10*(2), 909–934. https://doi.org/10.55214/2576-8484.v10i2.12272

Authors’ Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study’s findings are fully available within the article.

How to cite this article (APA)

Zhao, Y., Pimde, P., & Sukkamart, A. (2026). HOW ORGANIZATIONAL FOUNDATIONS SHAPE CHINESE AI INNOVATION PERFORMANCE. *Veredas Do Direito*, 23(6), e235758. https://doi.org/10.18623/rvd.v23.5758