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Research Article

The Influence of Knowledge Interaction and Open Innovation Ecosystems on Enterprise Innovation Performance in the Industrial Sector Using Structural Equation Modeling

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Abstract:

Amidst accelerated technological iteration and innovation paradigm restructuring in the industrial sector, this study investigates how the synergistic mechanism between knowledge interaction capability (KIC) and open innovation ecosystems (OIE) drives enterprise innovation performance (EIP). Utilizing survey data from 314 high-tech manufacturing firms in Zhejiang Province, China, we constructed a structural equation model (SEM) integrating confirmatory factor analysis (CFA) and Bootstrap sampling (5,000 repetitions). The model incorporates three KIC dimensions – knowledge assimilation capability (KAC), transformation capability (KTC), and sharing capability (KSC) – dual OIE embeddedness (relational embeddedness NRE; structural embeddedness NSE), and EIP. Model fit indices significantly exceeded thresholds (χ^2/df = 1.383, GFI = 0.907, CFI = 0.978, RMR = 0.044, RMSEA = 0.035). Core SEM path equations: EIP = 0.159·KAC + 0.164·KTC + 0.173·KSC + 0.247·NRE + 0.246·NSE, NSE = 0.294·KAC + 0.221·KTC + 0.180·KSC, NRE = 0.287·KAC + 0.215·KTC + 0.206·KSC. The results show that all three dimensions of KIC directly drive EIP (with KAC playing the most significant role), while the dual embeddedness of OIE plays a significant part of the mediating role, with KAC's mediating pathway through NSE contributing most prominently. This finding confirms the synergistic mechanism of "internal knowledge competence-external ecological embeddedness". The study provides differentiated innovation strategies for industrial sectors: technology-intensive firms need to strengthen ecological niche construction to activate knowledge assimilation, while R&D-intensive organizations should optimize internal knowledge sharing to achieve direct value transformation

1. Introduction

In the context of the profound reconstruction of the industrial competition paradigm, innovation has become the core engine for sustainable growth in enterprises.[1] Industrial sector firms, in particular, must respond to market changes through continuous product iteration and process innovation, highlighting the strategic value of Knowledge Interaction Capability (KIC)—the dynamic capability of firms to acquire, transform, and share knowledge resources to drive innovation.[2,3] However, innovation does not solely rely on internal capabilities; the Open

Innovation Ecosystem (OIE) plays a key role in shaping enterprise innovation outcomes by integrating external collaborations and partnerships. In addition to traditional forms of collaboration, OIE leverages structured collaborative networks to integrate complementary resources from external actors such as suppliers, customers, and research institutions, providing systemic innovation support for enterprises. [4-6] This perspective not only highlights the presence of external partners but also emphasizes the architectural coordination and interdependence characteristics inherent in the dynamics of the ecosystem.

Although the individual effects of Knowledge Interaction Capability (KIC) and Open Innovation Ecosystem (OIE) on Enterprise Innovation Performance (EIP) have been widely studied, [7-9] the synergy between the two remains a critical blind spot. Specifically, there are two key gaps: (1) Unclear Synergy: Can external collaboration networks amplify the innovative value of internal knowledge capabilities? In particular, does OIE play a mediating role between KIC and EIP, which remains systematically unverified? [10](2) Unknown Role Weights: The relative contribution of internal knowledge management capabilities and external ecosystem collaboration to innovation performance is not yet clarified, leading to a lack of guidance for resource allocation in enterprises. [11] This study aims to explore the moderating and mediating roles of the Open Innovation Ecosystem (OIE) in the dual dimensions of Network Relationship Embedding (NRE) and Network Structure Embedding (NSE), revealing how it mediates and enhances the impact of Knowledge Interaction Capability (KIC) on Enterprise Innovation Performance (EIP). This research seeks to fill the theoretical gap in "capability-ecosystem" synergy studies. Building on the latest advancements in Dynamic Capabilities Theory and Innovation Ecosystem Theory, [12,13] the study proposes an integrated analytical framework. It empirically tests, using Structural Equation Modeling (SEM), the direct and indirect paths through which the three dimensions of KIC (Knowledge Assimilation Capacity [KAC], Knowledge Transformation Capacity [KTC], Knowledge Sharing Capacity [KSC]) influence EIP via the dual embedding of OIE (NRE/NSE). This design will illuminate how firms can achieve systematic innovation performance improvement by strategically configuring external ecosystem positions and activating internal knowledge dynamics.

2. Methods

2.1 Research Design and Sample

This study focuses on technology-intensive enterprises in Zhejiang Province, China (with a total of 1,517 registered high-tech firms in the region). The target sample was selected based on three criteria: number of employees > 100, R&D investment in the past five years, and ownership of ≥5 patents. A total of 400 questionnaires were distributed through a combination of online surveys and in-person interviews, with 314 valid responses received (a response rate of 78.5%). The sample is highly representative of the characteristics of industrial innovation entities: the industry distribution is dominated by new energy (15.9%), automotive (14.0%), and aerospace (12.4%); the enterprise size is concentrated in medium and large firms (80.9% have 100-1,000 employees); in terms of innovation foundation, 79% of the firms have sustained R&D investment over the past five years, and 89.2% hold patents (with 35.0% owning 1-10 patents). This sample fully meets the requirements for structural equation modeling analysis (sample-to-variable ratio of 10:1), ensuring the power of subsequent statistical tests .[14,15]

2.2. Measurement Constructs and Scales

This study uses multi-dimensional scales to measure the core constructs: Knowledge Interaction Capability (KIC), Open Innovation Ecosystem (OIE), and Enterprise Innovation Performance (EIP). All scales were developed based on established literature and contextualized for the industrial innovation setting (see Table 1). The measurement employs a Likert scale (1 = strongly disagree, 5 = strongly agree). To ensure the validity of the questionnaire content, six experts in the industrial field were invited to review and confirm each question. All item scores exceeded 0.8, indicating that the scale has high quality. Constructs, Dimensions, and Measurement Descriptions are shown in table1.

Table 1 *Constructs, Dimensions, and Measurement Descriptions*

Construct	Dimension/Indicator	Description
Knowledge Interaction Capability (KIC)	**Knowledge Assimilation Capability (KAC)**	Ability to understand and integrate external knowledge
	Knowledge Transformation Capability (KTC)	Ability to adapt and apply acquired knowledge to new contexts.

Construct	Dimension/Indicator	Description
	Knowledge Sharing Capability (KSC)	Ability to effectively disseminate knowledge within and outside the firm.
Open Innovation Ecosystem (OIE)	**Network Relationship Embedding (NRE)**	The strength and quality of a firm's relationships with external partners.
	Network Structure Embedding (NSE)	The structural positioning of a firm within the broader innovation network.
Enterprise Innovation Performance (EIP)	A single latent variable reflecting the firm's success in innovation activities, including product development, adoption of new technologies, and market success.	

2.3 Conceptual Model and Hypotheses

The conceptual model for this study is designed to investigate the relationships between Knowledge Interaction Capability (KIC), Open Innovation Ecosystem (OIE), and Enterprise Innovation Performance (EIP). The model posits that KIC, through its dimensions (KAC, KTC, KSC), directly influences EIP.OIE mediates the relationship between KIC and EIP, with NRE and NSE serving as mediators. The conceptual model is shown in Figure 1. Based on the conceptual model, hypotheses are proposed as shown in Table 2.

2.4 Analytical Approach

This study employs a two-step Structural Equation Modeling (SEM) analysis framework, [16,17] using AMOS 27.0 software to perform the following procedures:

Step 1: Measurement Model Testing. Confirmatory Factor Analysis (CFA) is used to assess construct validity, including convergent validity (AVE > 0.5, CR > 0.7) [18] and discriminant validity (Fornell-Larcker criterion). Common method bias is tested using the Harman's single-factor method. [19,20]

Step 2: Structural Model and Mediation Testing. The four-step method proposed by Wen and Ye (2014) [21] combined with the Bootstrap method is used to test the mediation effects:

(1) Direct Effect Testing: Establish the KIC → EIP model to test H1.

(2) Capability → Ecosystem Path: Test KIC → OIE (H2).

(3) Ecosystem → Performance Path: Test OIE → EIP (H3).

Mediation Effect Quantification: Build the full path model and calculate the mediation effect using Bootstrap sampling (5000 iterations). If the 95% confidence interval (CI) does not contain 0, H4 is supported.

3. Results

3.1 Measurement Model Testing

3.1.1 Knowledge Interaction Capability (KIC) Measurement Model Testing

The CFA model fit for KIC is shown in Figure 2. The CFA results indicate that the KIC scale has a good overall fit ($\chi^2/df = 1.922$, RMSEA = 0.054, CFI = 0.977). The results of the validity and reliability tests are presented in Table 3. The factor loadings for each dimension are all greater than 0.64 ($p < 0.001$), and the AVE values (0.635–0.642) and CR values (0.877–0.895) meet the standards. Cronbach's α coefficients are all greater than 0.87, indicating good convergent validity and reliability. The square roots of the AVE for each dimension (0.797–0.801) are greater than the inter-factor correlations (with the highest being 0.655), demonstrating good discriminant validity of the factors.

3.1.2 Open Innovation Ecosystem Measurement Model Testing

The CFA model fit for the OIE is shown in Figure 3. The CFA results indicate that the OIE scale has a good overall fit ($\chi^2/df = 1.430$, RMSEA = 0.037, CFI = 0.993). The results of the validity and reliability tests are presented in Table 4. The factor loadings for each dimension are all greater than 0.63 ($p < 0.001$), and the AVE values (0.587–0.726) and CR values (0.876–0.930) meet the standards. Cronbach's α coefficients are all greater than 0.87, indicating good convergent validity and reliability. The square roots of the AVE for each dimension (NRE = 0.766; NSE = 0.852) are greater than the inter-factor correlations ($r = 0.523$, $p < 0.001$), demonstrating good discriminant validity for all factors.

3.1.2 Open Innovation Ecosystem Measurement Model Testing

The Confirmatory Factor Analysis (CFA) model fit for the Open Innovation Ecosystem (OIE) is shown in Figure 4. The CFA results indicate that the OIE scale exhibits a good overall fit ($\chi^2/df = 1.430$, RMSEA = 0.037, CFI = 0.993). The results of the validity and reliability tests are shown in Table 5. The factor loadings for each dimension are all

greater than 0.63 ($p < 0.001$), and the AVE values (0.587–0.726) and CR values (0.876–0.930) meet the required standards. Cronbach's α coefficients are all greater than 0.87, indicating good convergent validity and reliability. The square roots of the AVE for each dimension (NRE = 0.766; NSE = 0.852) are greater than the inter-factor correlations ($r = 0.523$, $p < 0.001$), demonstrating good discriminant validity for all factors.

3.2 Common Method Bias Assessment

Harman's single-factor method was used to test for common method bias. The results of the Confirmatory Factor Analysis (CFA) show that when all items were forced into a single-factor model, the fit indices significantly worsened ($\chi^2/df = 8.018$, GFI = 0.525, CFI = 0.585), far below acceptable standards (see Table 6). According to the criteria established by Tang and Wen (2020), these results indicate that there is no serious issue of common method bias in the data.

3.3 Structural Model and Hypothesis Testing

3.3.1 Analysis of the direct Impact of KIC on EIP

The results of the direct effect model fit are shown in Figure 5, with good model fit indices ($\chi^2/df = 1.648$, RMSEA = 0.045, CFI = 0.977), meeting the requirements for SEM analysis. The path analysis results are shown in Table 7. All three dimensions of KIC directly drive innovation performance, with Knowledge Assimilation Capability (KAC) having the strongest positive impact on EIP ($\beta = 0.298$, $p < 0.001$). Knowledge Transformation Capability (KTC) and Knowledge Sharing Capability (KSC) also significantly promote EIP ($\beta = 0.266/0.265$, $p < 0.001$), but their effects are weaker than that of KAC.

3.3.2 Analysis of the Impact of KIC on OIE

In the model examining the impact of independent variables on mediating variables, Knowledge Assimilation Capability, Knowledge Transformation Capability, and Knowledge Sharing Capability all directly affect Network Relationship Embedding and Network Structure Embedding. The model fit results are shown in Figure 6, with good fit indices ($\chi^2/df = 1.547$, RMSEA = 0.042, CFI = 0.976), allowing for result analysis.The main path fitting results of the model are shown in Table 8. All three dimensions of Knowledge Interaction Capability (KIC) significantly and positively drive the dual embedding of the Open Innovation Ecosystem (OIE). Among them, Knowledge Assimilation Capability (KAC) has the strongest standardized effect on Network Relationship Embedding and Network Structure Embedding. Knowledge Transformation Capability (KTC) and Knowledge Sharing Capability (KSC) also significantly promote NRE and NSE, but their effects are weaker than that of KAC.

3.3.3 Analysis of the Impact of OIE on EIP

In the model examining the impact of mediating variables on the dependent variable, Network Relationship Embedding and Network Structure Embedding in the Open Innovation Ecosystem directly influence Enterprise Innovation Performance. The model fit results are shown in Figure 7, with good fit indices ($\chi^2/df = 1.305$, RMSEA = 0.031, CFI = 0.992), allowing for result analysis.The main path fitting results of the model are shown in Table 9. Network Relationship Embedding significantly and positively influences Enterprise Innovation Performance (EIP) ($\beta = 0.445$, C.R. = 8.100, $P < 0.001$); Network Structure Embedding also significantly and positively influences EIP ($\beta = 0.485$, C.R. = 8.881, $P < 0.001$). In summary, both Network Relationship Embedding and Network Structure Embedding have a significant positive impact on Enterprise Innovation Performance.

3.4 Mediation Analysis

The independent variable, Knowledge Interaction Capability, directly influences the mediating variable, Open Innovation Ecosystem, and the dependent variable, Enterprise Innovation Performance. Meanwhile, the Open Innovation Ecosystem directly influences Enterprise Innovation Performance. The model fit results are shown in Figure 8, with good fit indices ($\chi^2/df = 1.383$, RMSEA = 0.035, CFI = 0.978), allowing for result analysis.

3.4.1 Main Path Analysis

The main path fitting results of the model (see Table 10) show that all hypotheses are supported. Specifically: KIC significantly influences EIP through all three dimensions, with KAC having the strongest impact. KIC also significantly impacts both NRE and NSE, supporting the hypothesized paths. NRE and NSE significantly influence EIP, with both paths showing strong positive relationships.Among these, the four paths with the strongest significance are: KAC → NRE, KAC → NSE, NRE → EIP, NSE → EIP. These paths show the highest path coefficients and statistical significance, with all having C.R. values exceeding 4.2 and P values less than 0.001, indicating their critical role in driving innovation performance.

In summary, the mediation model's results confirm the significant effects of all factors on innovation performance, supporting the proposed hypotheses.

3.4.2 Mediation Effect Analysis

Bootstrap testing (5000 samples) confirmed that Network Relationship Embedding (NRE) and Network Structure Embedding (NSE) both play significant mediating roles between Knowledge Interaction Capability (KIC) and Enterprise Innovation Performance (EIP) (all paths with 95% CI not including 0). Specifically (see Table 11):

Knowledge Assimilation Capability (KAC): The total effect is 0.302, with the mediating path contributing 47.4% (NRE path: 0.072 [0.028, 0.123]; NSE path: 0.071 [0.036, 0.108]), and the direct effect (0.159) is slightly higher than the mediation effect.

Knowledge Sharing Capability (KSC): The total effect is 0.268, with the direct effect being dominant (64.6%), and the NSE path (0.051 [0.012, 0.090]) contributing more than the NRE path (0.044 [0.005, 0.085]).

Knowledge Transformation Capability (KTC): The total effect is 0.271, with the direct effect accounting for 60.5% (0.164), and the mediation effect representing only 39.5% (NRE: 0.055; NSE: 0.053).Core Findings: KAC is most dependent on the mediating path (47.4%), while KSC is most dependent on the direct path (64.6%); NSE shows stronger effects across all three mediating paths.

4. Discussion

4.1 Differential Effects of Dual-Path Mechanisms

This study reveals a dual-path mechanism through which knowledge interaction capability (KIC) and open innovation ecosystems (OIE) synergistically drive enterprise innovation performance (EIP). Key findings demonstrate: (1) Knowledge assimilation capability (KAC)heavily relies on OIE's network embeddedness (particularly structural embeddedness, NSE), with its mediating path contributing47.4% of the total effect. This validates the pivotal role of external ecological networks as hubs for heterogeneous knowledge acquisition [22]. (2) Knowledge sharing capability (KSC)primarily drives EIP through direct pathways (direct effect:64.6%), highlighting the irreplaceable role of internal collaborative density in tacit knowledge transformation [23]. This discovery establishes a critical boundary condition for dynamic capability theory: The innovation value realization path of knowledge capabilities is modulated by their inherent attributes—assimilation requires ecological positioning, while sharing is rooted in internal coordination [3; 29].

4.2 Reconceptualizing Network Embeddedness Mediation

The theoretical contributions manifest in three dimensions:(1) Dominance of structural embeddedness (NSE): The average mediating contribution of NSE is 23.5%, surpassing that of Network Relationship Embedding (NRE), [24] indicating that ecological positioning has a stronger impact in amplifying the benefits of knowledge assimilation than bilateral relationships. This study finds that the mediating dominance of NSE (47.4% contribution) aligns with the observed technological ecosystem effects in the wearable device industry by Wang et al. (2025),[25] establishing a cross-domain connection.(2) Unique duality of knowledge transformation capability (KTC): KTC is the only dimension exhibiting a "direct + partial mediation" dual channel (direct effect:60.5%), reflecting its transitional nature bridging internal and external synergies.[26] (3) Strategic implications of path weights: The divergence between KAC and KSC pathways (direct effects:52.6% vs. 64.6%) provides precise navigation for innovation resource allocation.[27; 28; 30].

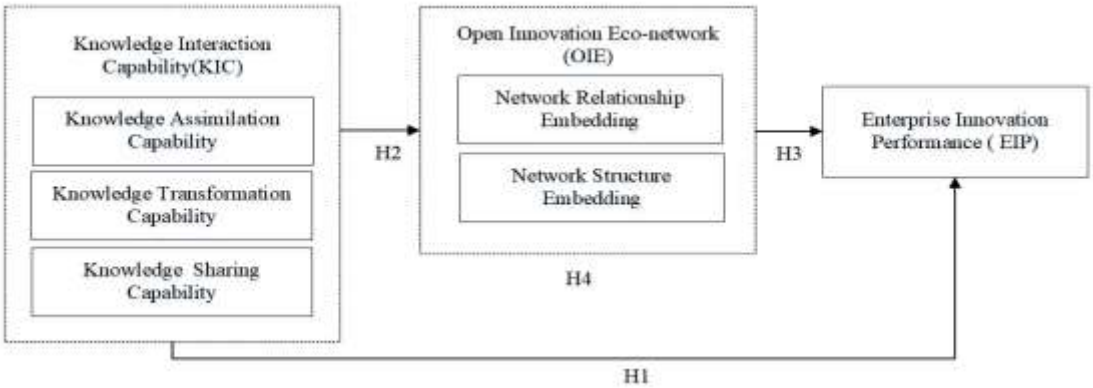


Figure 1 *Conceptual Models*

Table 2 *Summary of Research Hypotheses*

No	Hypothesis
H1	Knowledge Interaction Capability, as measured by KAC, KTC, and KSC, has a direct positive effect on Enterprise Innovation Performance.
H2	Knowledge Interaction capability positively affects the open innovation Eco-networks, including both NRE and NSE.
H3	The open innovation Eco-networks, in terms of both NRE and NSE, positively affect Enterprise Innovation Performance.
H4	Both NRE and NSE mediate the relationship between KIC and EIP, thus enhancing the impact of KIC on innovation performance.

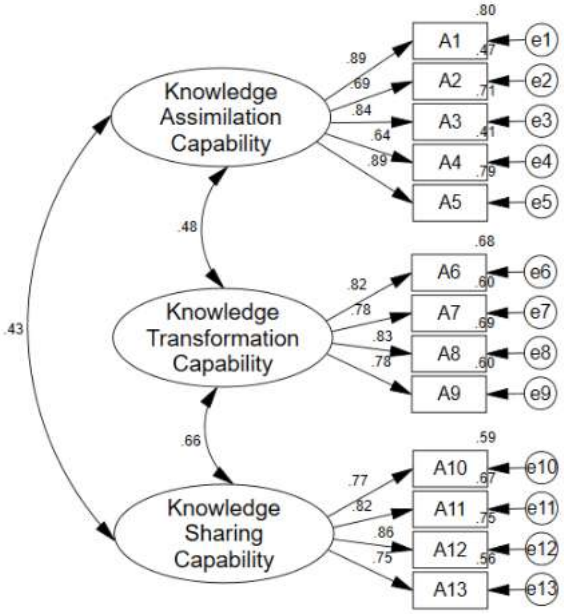


Figure 2 *Validated Factor Analysis Model of Knowledge Interaction Capability (KIC)*

Table 3 *Reliability and Validity Test Results of the KIC Scale*

Dimension	AVE	CR	Cronbach's α	Loadings Range	$\sqrt{\text{AVE}}$
KAC	0.635	0.895	0.890	0.643–0.892	0.797
KTC	0.641	0.877	0.876	0.775–0.829	0.800
KSC	0.642	0.877	0.875	0.747–0.864	0.801

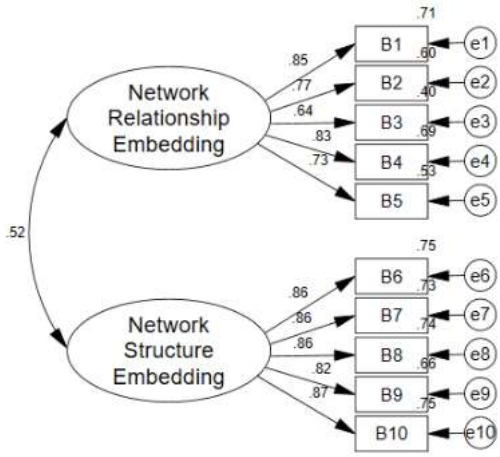


Figure 3 *Validated Factor Analysis Model of Open Innovation Eco-network (OIE)*

Table 4 *Reliability and Validity Test Results of the OIE Scale*

Dimension	AVE	CR	Cronbach's α	Loadings Range	$\sqrt{\text{AVE}}$
NRE	0.587	0.876	0.873	0.636–0.845	0.766
NSE	0.726	0.930	0.929	0.815–0.867	0.852

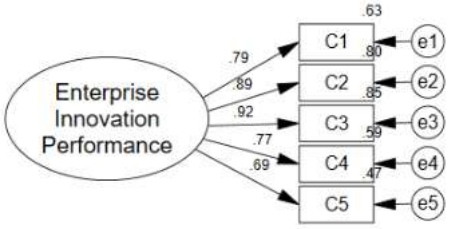


Figure 4 *Validated Factor Analysis Model of EIP*

Table 5 *Reliability and Validity Test Results of the EIP Scale*

Dimension	AVE	CR	Cronbach's α	Loadings Range
EIP	0.666	0.908	0.904	0.6687–0.919

Table 6 *Harman single factor test*

Indicator	χ2	df	χ2/df	RMR	RMSEA	GFI	NFI	TLI	CFI
Fitting value	2806.306	350	8.018	0.092	0.150	0.525	0.554	0.551	0.585
Fitting standard			1~3	＜0.08	＜0.08	＞0.9	＞0.9	＞0.9	＞0.9

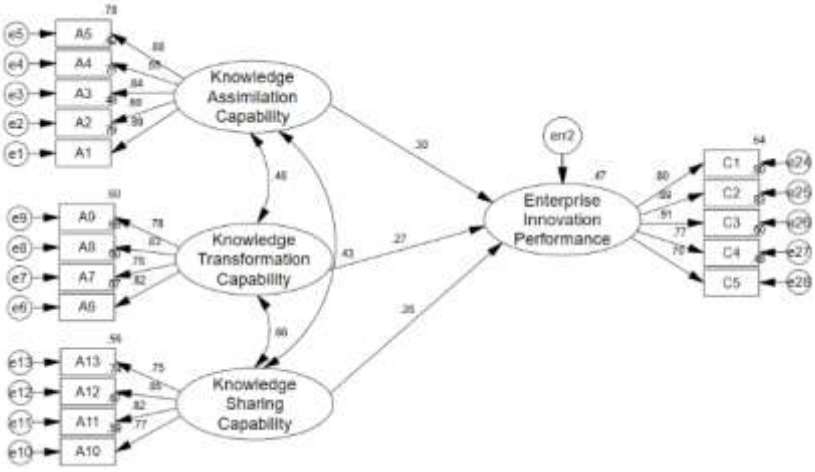


Figure 5 *Relational model of the impact of* KIC *on EIP*

Table 7 *Direct Impact of KIC on EIP (Standardized Estimates)*

Impact Path	β	SE	C.R.	P-value
KAC→EIP	0.298	0.044	5.147	＜0.001***
KTC→EIP	0.266	0.06	3.595	＜0.001***
KSC→EIP	0.265	0.066	3.684	＜0.001***

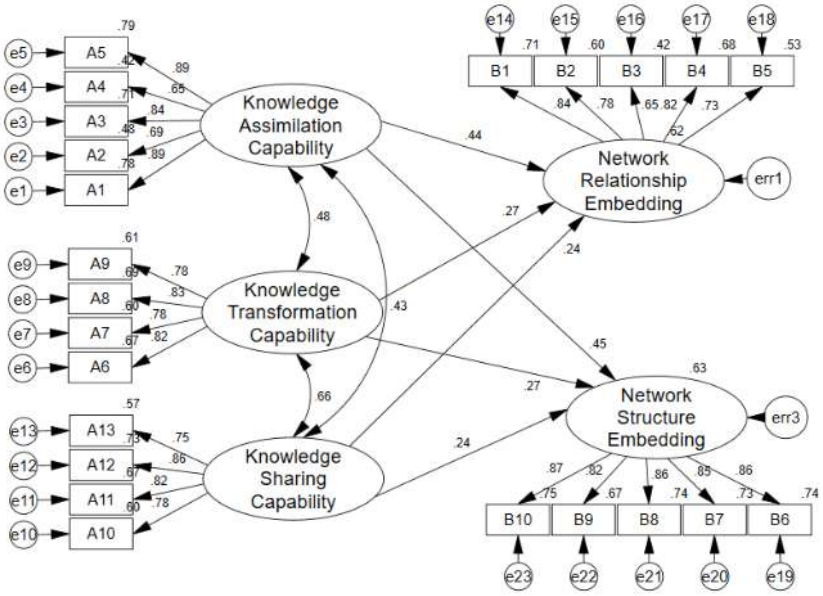


Figure 6 *Relational model of the impact of* KIC *on OIE*

Table 8 *The Impact of KIC on OIE*

Impact Path	β	SE	C.R.	P-value
KAC→NSE	0.453	0.054	8.722	＜0.001***
KTC→NSE	0.271	0.071	4.195	＜0.001***
KSC→NSE	0.236	0.077	3.794	＜0.001***
KAC→NRE	0.44	0.055	8.046	＜0.001***
KTC→NRE	0.273	0.072	3.997	＜0.001***
KSC→NRE	0.241	0.079	3.659	＜0.001***

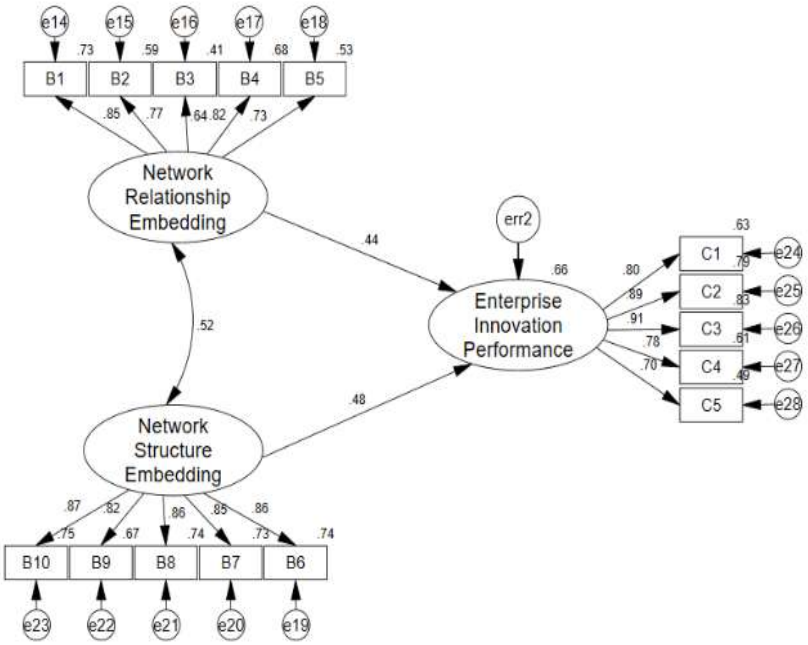


Figure 7 *Relational model of the impact of OIE on EIP*

Table 9 *The Impact of OIE on EIP*

Impact Path	β	SE	C.R.	P
NSE→EIP	0.485	0.04	8.881	＜0.001
NRE→EIP	0.445	0.041	8.1	＜0.001

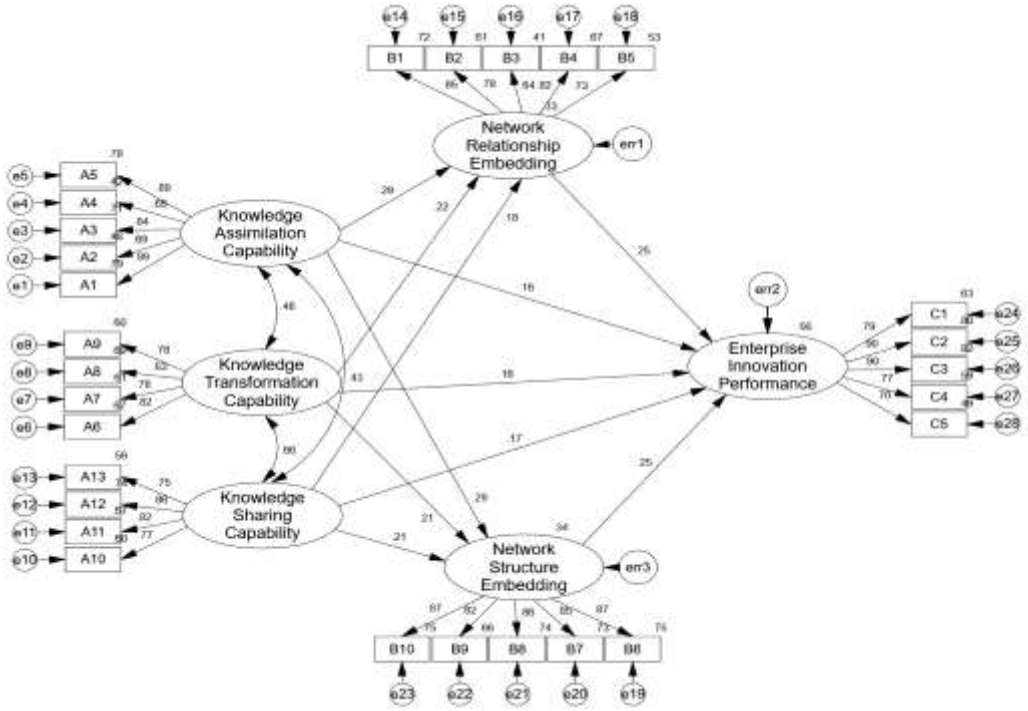


Figure 8 *The mediating role model of OIE between KIC and EIP*

Table 10 *Main path fitting results of the mediation model*

Hypothesis	Impact Path	Estimate	SE	C.R.	P	Conclusion
H2-1a	KAC→NRE	0.294	0.065	4.564	＜0.001	Support
H2-1b	KAC→NSE	0.287	0.064	4.648	＜0.001	Support
H2-2a	KTC→NRE	0.221	0.089	2.67	0.008	Support
H2-2b	KTC→NSE	0.215	0.088	2.698	0.007	Support
H2-3a	KSC→NRE	0.18	0.097	2.249	0.025	Support
H2-3b	KSC→NSE	0.206	0.096	2.683	0.007	Support
H1-1	KAC→EIP	0.159	0.043	2.78	0.005	Support
H1-2	KTC→EIP	0.164	0.056	2.349	0.019	Support
H1-3	KSC→EIP	0.173	0.061	2.575	0.01	Support
H3-1	NRE→EIP	0.247	0.043	4.298	＜0.001	Support
H3-2	NSE→EIP	0.246	0.041	4.38	＜0.001	Support

Table 11 *Mediation Effect Decomposition Summary*

Predictor Variable	Total Effect	Direct Effect	Total Mediation Effect	NRE Path [95% CI]	NSE Path [95% CI]

Predictor Variable	Total Effect	Direct Effect	Total Mediation Effect	NRE Path [95% CI]	NSE Path [95% CI]
KAC	0.302	0.159	0.143	0.072[0.028,0.123]	0.071[0.036,0.108]
KTC	0.271	0.164	0.107	0.055[0.013,0.102]	0.053[0.011,0.097]
KSC	0.268	0.173	0.095	0.044[0.005,0.085]	0.051[0.012,0.090]

5. Conclusions

This study empirically verifies through structural equation modeling that dual-engine drivers enhance enterprise innovation performance (EIP): Knowledge sharing capability (KSC) exerts core effects through direct pathways, Network structural embeddedness (NSE) serves as the pivotal hub transforming knowledge assimilation capability (KAC) into innovation outcomes. This path divergence stems from the inherent nature of knowledge capabilities: KAC, as an outward-oriented capability, depends on a firm's structural positioning within innovation ecosystems; KSC, as an inward-oriented capability, relies on collaborative density and cultural capital within organizations.

We thus propose the Capability-Ecosystem Alignment Model (CEAM): For technology-acquiring firms, prioritize building NSE to capture technological dividends by occupying core ecosystem nodes; For R&D-intensive organizations, focus on internal collaborative systems to maximize direct value from tacit knowledge flows. This model transcends the traditional "capability versus ecosystem" dichotomy, providing a dynamic balancing framework for innovation strategies.

Future research should track the co-evolution of knowledge capabilities and ecological embeddedness, particularly examining contingency patterns of dual-path mechanisms in emerging industrial sectors (e.g., hydrogen energy, quantum computing), refining context-specific innovation management theories.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.
- **Use of AI Tools:** The author(s) declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

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