STRUCTURAL DETERMINANTS OF ENTERPRISE INNOVATION USING A SOCIAL NETWORK ANALYSIS APPROACH

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Abstract

This study employs Social Network Analysis (SNA) to investigate the structural mechanisms that influence Enterprise Innovation Performance (EIP) within an open innovation ecosystem. Based on expert judgment data, a Knowledge Interaction Network model was constructed. The results reveal 220 edges in the network, indicating complex relationships among the 20 factors. The network density is 0.703, and the average distance between nodes is 1.468, suggesting high interconnections and a significant impact on innovation performance. Quantitative analysis of key indicators, such as degree centrality, betweenness centrality, and closeness centrality, reveals a core-periphery network topology. The study finds that critical factors, such as Knowledge Absorption Efficiency (A2) and Cross-functional Collaboration (B3), occupy central positions and play pivotal roles in knowledge diffusion and cross-boundary integration. These core nodes not only facilitate knowledge flow and coordination but also emphasize that innovation performance depends not only on the presence of specific capabilities but also on their structural embeddedness within the network. This study advances the theoretical understanding of the capability-structure-performance mechanism in innovation management, offering practical guidance to enterprises seeking to enhance their innovation capabilities through strategic network positioning.

Keywords: enterprise innovation performance, social network analysis, knowledge interaction network, structural embeddedness

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Introduction

Enterprise innovation performance (EIP) is shaped not only by internal capabilities but also by complex, interdependent factors within a broader innovation ecosystem. Recent innovation management research highlights that innovation is not the result of isolated factors but emerges from the coordinated functioning of elements such as organizational learning, cross-functional collaboration, platform engagement, resource integration, and knowledge recombination (Huggins et al., 2020). These factors form relational networks that mediate the unfolding of innovation outcomes, with structural configurations playing a critical role in determining how these capabilities interact.

Traditionally, research has treated these factors as independent variables, often overlooking their structural interdependencies (Jansen & Zietsma, 2021). From an open innovation ecosystem perspective, innovation is not a linear process confined within firm boundaries, but rather a distributed process across dynamic networks (Vanhaverbeke & Cloodt, 2022; Tushman & O'Reilly, 2023; Bogers et al., 2023). Social Network Analysis (SNA), rooted in graph theory and relational sociology, offers a powerful framework for studying these structural relationships, revealing key nodes that influence knowledge diffusion and innovation performance (Uzzi & Spiro, 2005; Chesbrough & Bogers, 2024).

However, there is a gap in the literature regarding the structural analysis of innovation performance. Most studies overlook how innovation capabilities interact within systemic structures and fail to examine these relationships through an SNA lens. In light of this, the present study aims to explore the structural mechanisms affecting enterprise innovation performance within the context of open innovation ecosystems from a social network perspective. The specific research objectives are as follows: (1) To construct an interactive network of innovation-enabling factors and reveal their structural relationships. (2) To identify core nodes, bridging positions, structural holes, and other features within the network, and analyze their roles in knowledge diffusion and innovation generation. (3) To integrate both capability-based and structure-based perspectives in exploring the impact of network configuration on enterprise innovation performance.

Methodology

1. Construction of the Factor System

To examine the structural mechanisms driving enterprise innovation performance (EIP), this study first developed a multi-dimensional factor system that reflects both internal knowledge capabilities and external relational embedding. This dual perspective is grounded in prior research emphasizing that innovation outcomes result not only from what firms know, but also from how they interact within broader innovation ecosystems.

Internally, knowledge interaction capability (KIC), comprising knowledge assimilation, transformation, and sharing, enables continuous learning and knowledge-based innovation (Zahra & George, 2002; Crossan & Apaydin, 2010). Externally, firms operate within open innovation eco-networks (OIE), where structural factors such as relational strength, trust, openness, network centrality, and platform integration significantly influence knowledge flow and access to diverse resources (Laursen & Salter, 2006; Huggins et al., 2020).

To ensure the content validity of the factor system, this study is grounded in an integrated theoretical framework that synthesizes internal knowledge foundations with external network embeddedness. Specifically, the Knowledge Interaction Capability (KIC) dimension is conceptualized through the core lineage of Absorptive Capacity Theory. The operationalization of Knowledge Assimilation Capability (A1-A4) is derived from Zahra and George's (2002) seminal work, which delineates the processes of knowledge acquisition and internalization. Knowledge Transformation Capability (B1-B4), in turn, aligns with Crossan and Apaydin's (2010) multidimensional framework for organizational innovation, which focuses on the internal combination and application of knowledge. Meanwhile, the measures for Knowledge Sharing Capability (C1-C4) are informed by the insights of Inkpen and Tsang (2005), who illuminate the mechanisms of knowledge transfer from a social capital perspective. Concurrently, the Open Innovation Eco-network (OIE) dimension is deeply rooted in social network theory. The assessment of Network Relationship Embedding (D1-D4) draws upon Granovetter's (1985) concept of relational embeddedness, emphasizing the pivotal role of trust, frequent interaction, and resource ties. The conceptualization of Network Structure Embedding (E1-E4) integrates

Burt's (1992) theory of structural holes with Freeman's (1978) metrics of network centrality, aiming to capture the critical positional and structural advantages a firm holds within the overarching innovation network.

Building on this theoretical foundation, 20 innovation-related factors were identified across the two dimensions of KIC and OIE, as shown in Table 1. Each factor was assigned a code (e.g., A2 = Knowledge Absorption Efficiency) and served as a node in the social network analysis. This factor system provides the structural basis for analyzing the interdependencies among innovation drivers within the network.

Table 1 System of factors influencing enterprise innovation performance.

Primary factors	Secondary factors	Factors	No
Knowledge Interaction Capability (KIC)	Knowledge Assimilation Capability (KAC)	Diversity of knowledge acquisition capacity	A1
		Efficiency of knowledge absorption	A2
		Cross-sectoral knowledge integration mechanisms	A3
		Internalization of knowledge validates competence	A4
	Knowledge Transformation Capability (KTC)	Diversity of knowledge application scenarios	B1
		Speed of knowledge commercialization	B2
		Cross-functional collaboration capacity	B3
		Technology adaptation improvements	B4
	Knowledge Sharing Capability (KSC)	Frequency of use of shared platforms	C1
		Employee willingness to share	C2
		Sharing depth across organizations	C3
		Shared feedback mechanisms	C4
Open Innovation Eco-network (OIE)	Network Relationship Embedding (NRE)	Strength of trust in cooperation	D1
		Frequency of information interactions	D2
		Resource complementarity	D3
		Conflict resolution efficiency	D4
	Network Structure Embedding (NSE)	Nodal centrality	E1
		Structural cavity occupies	E2
		Network openness	E3
		Subgroup connectivity	E4

2. Data Collection and Matrix Formation

To capture the perceived interdependencies among innovation-related factors, this study employed a structured expert evaluation approach. A panel of ten experts was purposively selected based on the following stringent criteria: (1) a minimum of 15 years of professional experience in domains directly related to innovation management, R&D, or technology strategy; (2) holding a senior professional title (e.g., Professor, Senior Engineer) or a middle-to-senior management position (e.g., R&D Director, Head of Innovation); (3) representing diverse perspectives from both academia (5 experts) and high-tech industries (5 experts), including sectors such as automotive, aerospace, and electronics. This small but highly qualified expert panel is consistent with established methodologies for eliciting reliable judgments in complex systems where empirical data is scarce, such as the Delphi technique and Decision Making Trial and Evaluation Laboratory (DEMATEL) studies (Hsu & Sandford, 2007). The experts were invited to assess the strength of influence between all possible pairs of factors.

The aggregated scores were compiled into a 20×20 weighted, directed adjacency matrix, reflecting the collective view of factor interrelationships. This matrix served as the basis for the subsequent social network analysis, enabling a quantitative examination of the structural properties of the innovation system.

3. Network Modeling and Visualization Tools

To analyze the structure of the innovation factor network, the weighted adjacency matrix was processed using UCINET 6.0 for network metrics and NetDraw for visualization (Borgatti et al., 2013). In the network, each node represents an innovation factor, and each directed edge indicates the influence of one factor on another, with the edge thickness reflecting the strength of that influence.

This method allows for systematic mapping of the relational structure among factors, capturing both the density and directionality of interactions. Unlike traditional linear models, this approach highlights the interconnected and networked nature of innovation dynamics (Wasserman & Faust, 1994).

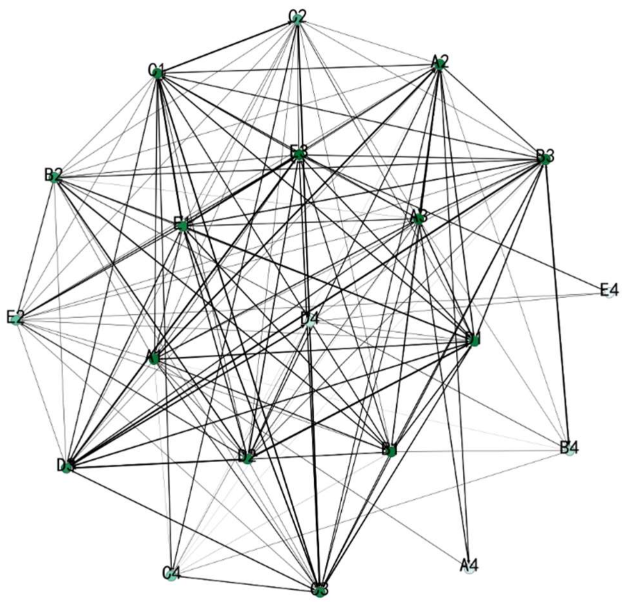

Figure 1 Innovation Factor Interaction Network

The Knowledge Interaction Network model was constructed in UCINET, and the results are shown in Figure 1. To quantitatively analyze the structural characteristics of this network, key metrics were computed using standard methods in social network analysis (Wasserman & Faust, 1994). The total number of edges represents the count of all directed connections between nodes. Network density is defined as the ratio of actual edges to the maximum possible number of edges in a directed network, calculated using the formula 1:

$$D = \frac{L}{N(N-1)} \tag{1}$$

Where L is the number of existing edges, and N is the number of nodes. The average distance is the mean of the shortest path lengths between all reachable pairs of nodes. Specifically, our analysis identified 220 edges, indicating a high degree of complexity in the relationships among the 20 factors. The network density is 0.703, which is significantly higher than 0.5, indicating a highly complex network with tight interconnections among factors. The average distance between nodes in the network is 1.468, indicating a high degree of ease in the interaction and influence among the factors.

4. Centrality Metrics

To identify the most influential elements in the innovation network, classical centrality indicators were computed, including out-degree, betweenness, and closeness (Freeman, 1978; Borgatti & Everett, 2006). These metrics provide insight into which nodes exert the most significant structural influence and play coordinating roles in the knowledge interaction process. Out-degree centrality measures the number of direct outgoing connections from a node, reflecting its ability to exert influence over other factors. Betweenness centrality captures the extent to which a node lies on the shortest paths between other nodes, indicating its role as a bridge or coordinator. Closeness centrality measures the ease with which a node can reach all others in the network, indicating its overall accessibility. These metrics provide complementary perspectives on a factor's strategic position in the network. Nodes with high values on these indicators are likely to play key roles in knowledge propagation, resource coordination, and system-wide connectivity, all of which are closely associated with enhanced innovation outcomes (Faridian & Neubaum, 2019).

5. Structural Hole Metrics

To move beyond surface-level influence and reveal latent coordination dynamics, this study further assessed the brokerage potential of network nodes using Burt's (1992) structural hole framework. Brokerage roles are crucial for connecting otherwise unconnected knowledge domains and facilitating cross-boundary innovation.

Three structural indicators were calculated to evaluate each node's brokerage capacity:

(1) Effective size, which reflects the number of non-redundant ties a node maintains, indicating the diversity of its connections.

(2) Efficiency, representing the ratio of adequate size to total degree, shows how effectively a node leverages its relationships.

(3) Constraint, a measure of relational redundancy, where lower values signal greater structural autonomy and potential to act as a broker.

Nodes with a high adequate size and low constraint are well positioned to bridge otherwise disconnected subgroups, thereby facilitating the transfer, recombination, and diffusion of novel knowledge. These so-called knowledge brokers play a vital role in enhancing innovation outcomes by accessing heterogeneous resources and mediating between otherwise isolated domains (Granovetter, 1985; Inkpen & Tsang, 2005).

6. Cohesive Subgroup Analysis

To uncover potential modularity and role differentiation within the innovation network, the study employed CONCOR (Convergence of Iterated Correlations) clustering. This method partitions nodes based on structural equivalence, grouping factors that share similar patterns of relational ties (Wasserman & Faust, 1994).

The resulting cohesive subgroups reflect a functionally differentiated structure within the network. Some clusters are characterized by tightly interconnected nodes that engage in knowledge assimilation and internal exchange, thereby forming the cognitive core of the system. Others occupy intermediary positions that bridge distinct modules and facilitate cross-domain coordination. A third type of subgroup includes more loosely connected factors that provide complementary support or specialized services at the periphery.

This layered and distributed configuration aligns with the logic of open innovation ecosystems, in which innovation arises from the interaction among differentiated roles rather than from isolated actors. Recognizing such modularity offers practical value for strategic resource allocation and targeted policy interventions (Provan et al., 2007).

Results

The Knowledge Interaction Network model (Figure 1) visually illustrates the high interconnectivity among the 20 factors. The dense web of connections directly reflects the high network density (0.703) and the substantial number of relational pathways (220 edges), as quantified later. This complexity underscores that innovation arises from a system of interdependent factors rather than from isolated elements.

1. Centrality Analysis Results

The centrality analysis highlights several key nodes that play dominant roles in the innovation factor network. In particular, Knowledge Absorption Efficiency (A2), Knowledge Internalization & Reuse (A3), and Cross-Functional Collaboration (B3) consistently rank highest across the three centrality metrics: out-degree, betweenness, and closeness. Table 2 presents the top ten factors ranked by their centrality measures.

The table highlights how these nodes serve as both influential drivers and structural coordinators within the network.

Table 2 Key centrality measures of innovation factors.

Factor Cod	Factor Name	Out-Degree	Betweenness Centrality	Closeness Centrality
A2	Knowledge Absorption Efficiency	14.10	72.4	0.683
A3	Knowledge Internalization & Reuse	12.75	69.8	0.670
B3	Cross-Functional Collaboration	13.40	81.6	0.691
A1	Knowledge Acquisition Diversity	13.20	55.1	0.672
E3	Network Openness	12.90	66.2	0.664
D1	Trust-Based Cooperation	11.85	50.3	0.659
C2	Platform Integration Capability	10.95	42.7	0.648
D2	Inter-Organizational Trust	11.10	47.8	0.652
B1	Knowledge Transfer Process Optimization	9.85	39.2	0.640
E1	Network Centrality Awareness	9.35	36.5	0.632

These results suggest that A2 and A3 constitute the core of the internal knowledge interaction capability, driving innovation by enabling firms to absorb and restructure knowledge acquired from external sources effectively. Meanwhile, B3 serves a critical organizational role by facilitating cross-functional knowledge flows, ensuring that knowledge is not siloed within departments but is instead mobilized throughout the enterprise.

In network terms, these nodes act not only as influencers (via out-degree) but also as connectors (via betweenness) and rapid disseminators (via closeness). Their structural prominence aligns with prior research, which emphasizes that both the depth of knowledge and the ease of organizational diffusion are vital to the success of innovation (Cohen & Levinthal, 1990; Crossan & Apaydin, 2010).

2. Structural Hole Analysis Results

Beyond centrality, the analysis of structural holes provides deeper insight into the brokerage functions of these same core factors. According to Burt’s theory (1992), nodes that bridge disconnected groups without redundancy can serve as strategic knowledge brokers within the system.

To quantify brokerage potential, three structural hole indicators were calculated: adequate size, efficiency, and constraint. These results are presented in Table 3, which highlights the top-performing nodes in terms of their ability to span gaps and connect previously unlinked parts of the network.

Table 3 Structural hole indicators of selected factors.

Factor Code	Factor Name	Effective Size	Efficiency	Constraint	Hierarchy
A2	Knowledge Absorption Efficiency	5.80	0.72	0.22	0.35
A3	Knowledge Internalization & Reuse	5.67	0.70	0.25	0.33
B3	Cross-Functional Collaboration	6.02	0.75	0.19	0.29
D2	Inter-Organizational Trust	4.80	0.64	0.31	0.41
E3	Network Openness	5.10	0.68	0.27	0.38
A1	Knowledge Acquisition Diversity	5.25	0.69	0.28	0.36

The same three factors A2, A3, and B3 exhibit strong brokerage potential, characterized by:

(1) High effective size, indicating access to diverse, non-overlapping sources of knowledge.

(2) High efficiency, reflecting optimal utilization of network connections.

(3) Low constraint, meaning reduced redundancy among their ties and greater structural autonomy.

While centrality reflects their visibility and influence, structural hole metrics reveal how these nodes function as relational bridges, facilitating the recombination of heterogeneous knowledge. This dual role, being both influential and structurally flexible, makes them pivotal to sustaining both incremental and exploratory innovation within the ecosystem (Granovetter, 1985; Inkpen & Tsang, 2005).

3 Subgroup Clustering Results

To further explore the underlying structure of the innovation factor network, this study employed CONCOR (Convergence of Iterated Correlations) clustering to identify cohesive subgroups. This method groups nodes based on structural equivalence, defined as similarity in their relational patterns with other nodes (Wasserman & Faust, 1994). The resulting clusters reveal distinct modular structures within the network, each reflecting a functionally differentiated role in the innovation ecosystem.

The analysis identified five cohesive subgroups, each characterized by varying levels of internal density and functional orientation. These subgroups are summarized in Table 4.

Table 4 Cohesive subgroups based on structural equivalence.

Subgroup	Included Factors	Functional Role Description
Group 1	A1, A2, A3	Core knowledge assimilation and absorption
Group 2	B1, B2, C1, D3	Knowledge process coordination
Group 3	B3, D1, D2	Trust-based bridge and collaboration
Group 4	C2, C3, E1, E2	Platform integration and network positioning
Group 5	A4, B4, D4, E4	Peripheral knowledge support

Group 1: functions as the core knowledge engine, responsible for acquiring, absorbing, and internalizing external knowledge into the organizational system.

Group 2: includes factors related to the coordination and optimization of knowledge processes, supporting the operational integration of knowledge across units.

Group 3: comprises nodes with strong brokerage and trust-building roles, facilitating collaboration and serving as structural bridges within the network.

Group 4: reflects the firm's embeddedness in external innovation platforms, highlighting the importance of openness, positioning, and network strategy.

Group 5: while structurally peripheral, it likely contributes to niche expertise and flexible support functions within the broader innovation system.

It is important to note that the total number of factors listed across the five subgroups in Table 4 exceeds 20. This is a characteristic outcome of the CONCOR algorithm, which partitions nodes into groups based on structural equivalence (i.e., similarity in their connection patterns to other nodes) rather than mutual exclusivity. A single factor can be structurally equivalent to members of different subgroups when considered in terms of its overall role in the network, leading to its inclusion in analyses of multiple clusters. This reflects the multifaceted roles that key factors play within the innovation ecosystem.

The modular structure revealed by this analysis highlights the distributed and systemic nature of enterprise innovation, in which multiple groups of factors play complementary and interdependent roles (Provan et al., 2007; Huggins et al., 2020). From a practical standpoint, this implies that policy and managerial interventions should target not only individual factors but also the relational configurations and functional roles of subgroups within the innovation ecosystem.

Discussions

This study introduces a Structure–Capability–Performance (SCP) framework to bridge the identified research gap, moving beyond linear models by systematically integrating micro-level capabilities with macro-level network structures. The core finding that innovation performance is codetermined by what a firm can do and where its capabilities are located in the interaction network offers a more nuanced explanation for innovation success in open ecosystems.

The consistent prominence of Knowledge Absorption Efficiency (A2), Cross-sectoral Knowledge Integration Mechanisms (A3), and Cross-functional Collaboration Capacity (B3) across all analyses vividly illustrates this framework. Their high centrality confirms their role as influential drivers, while their optimal structural hole metrics (high adequate size, low constraint) reveal a critical dual role: they are not only powerhouses of knowledge but also pivotal relational bridges. This function of occupying strategic brokerage positions to enable knowledge recombination is a critical mechanism for innovation, consistent with recent theoretical advancements on managing structural holes in ecosystems (Kotlar et al., 2024). This dual role, uncovered through the combined use of centrality and structural hole analyses, indicates that these factors possess structural autonomy to broker connections, recombine heterogeneous knowledge, and control information flows. This finding underscores that the structural embeddedness of knowledge capabilities within a network is a decisive factor for innovation, as highlighted in recent studies on knowledge management in innovation networks (Giannopoulou et al., 2024).

Furthermore, the cohesive subgroup analysis confirms the distributed nature of open innovation. The identification of five functionally differentiated subgroups suggests that managerial and policy interventions should target relational configurations and functional roles rather than individual factors. For instance, managers could:

Fortify the trust-based bridge (Group 3: B3, D1, D2) by investing in alliance management and trust-building mechanisms.

Enhance the core knowledge engine (Group 1: A1, A2, A3) through targeted R&D and personnel training.

Integrate peripheral support factors (Group 5) into the core network to prevent the loss of niche expertise.

From a theoretical perspective, this study embeds structural network analysis directly into innovation performance modeling, demonstrating that the interplay between capability and structure is multiplicative rather than additive. In practice, it provides a diagnostic map for firms to identify and strengthen their strategic central and brokering capabilities, and for policymakers to facilitate connectivity, particularly for peripheral actors.

In sum, the proposed Structure – Capability – Performance (SCP) framework provides a theoretically grounded and empirically supported explanation for how innovation is generated, diffused, and sustained in open systems. It lays a conceptual foundation for further research and offers actionable guidance for strategy design and innovation network governance.

Conclusions

This study has employed Social Network Analysis (SNA) to map the complex network of factors that drive enterprise innovation performance (EIP). Our findings, based on a network of 20 factors encompassing both knowledge interaction capabilities and the open innovation ecosystem, achieve the three core objectives of this research.

The analysis reveals that innovation performance stems not only from robust internal capabilities but also critically from their structural embeddedness. We identified Knowledge Absorption Efficiency (A2), Cross-sectoral Knowledge Integration Mechanisms (A3), and Cross-functional Collaboration Capacity (B3) as linchpins of the network. These factors play a dual role: they are powerful due to their central influence, but also act as essential relational bridges, a function highlighted by combining centrality and structural hole analyses.

The discovery of a modular structure through subgroup analysis further supports the conclusion that innovation is a distributed process. This implies that managers should focus on nurturing the functional roles of entire subgroups, for instance, by reinforcing trust-based bridges rather than optimizing factors in isolation.

Synthesizing these insights, we propose the Structure–Capability–Performance (SCP) framework to integrate micro-level capabilities with macro-level network structures. While the expert-derived model offers a robust conceptual foundation, it also points the way for future research to incorporate empirical interaction data and longitudinal tracking, which would further validate and dynamize the proposed framework.

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