Boundary spanning strategy and tacit knowledge recombination: analysis of joint-patent networks of patent-intensive firms

Abstract: The paper aims to investigate how balancing boundary spanning along with tacit knowledge recombination, particularly to achieve patent-intensive (PI) firms' goal of technological innovation. Under the framework of knowledge recombination, we propose that the external acquisition and recombination of tacit knowledge from knowledge-creating alliances in the joint-patent networks operate as a boundary-spanning mechanism that critically impacts the subsequent technology outputs. An inductive research technique is adopted for the methodology, demonstrated by the exploratory case study of Chinese PI firms that are knowledge-based economic actors. This paper collects 103 sample firms' 2015 to 2019 data through data envelopment analysis to measure their technical innovation performance and social network analysis to build joint-patent networks and explore knowledge-creating alliance relationships. Based on embedding analysis of technology innovation performance and joint-patent networks by data visualization, the relationship between innovation performance and boundary spanning is identified and distinguished by industry. Then, for each industry boundary-spanning strategy, the relationship between tacit knowledge recombination and position advantages is investigated and discussed in-depth through representative ego-networks study. The article highlights how tacit knowledge recombination works as a mechanism of boundary spanning. It emphasizes the significance of strategic balancing networks' position to improve technical innovation performance and competitiveness of PI firms. This research contributes to shedding additional light on the nature of the boundary-spanning mechanism and PI firms' knowledge exchanges. Specifically, it examines how balancing boundaries spanning through joint-patent networks can influence the processes of tacit knowledge transmission and recombination between knowledge-based actors.

Keywords: Boundary spanning, Tacit knowledge recombination, Joint-patent networks, Patent-intensive firms, Innovation performance

1. Introduction

Knowledge is widely recognized as a key factor in the creation of economic value and competitive advantage for organizations, according to the strategic management literature(Barney, 1991; Leonard, 1995). In the era of an information economy, with the acceleration of the flow of knowledge resources and the dependence of innovators on knowledge resources, there is an explosive demand for knowledge strategic management(M.-H. Chen et al., 2018). Particularly, knowledge access and utilize are most essential strategies.

As for knowledge access, mounting research has been devoted to *boundary-spanning* strategy, mainly through acquiring explicit knowledge outside, embedded in the form of patent acquisition, and synthesizing into new inputs(Caviggioli & Ughetto, 2013; De Marco et al., 2017; Figueroa & Serrano, 2019; Leone et al., 2022; Serrano, 2010), and explore. The company can achieve a greater impact in terms of entering new markets, technological repositioning, and subsequent technological development through boundary spanning(Helfat, 1994; Levinthal & March, 1993; Martin & Mitchell, 1998; Rosenkopf & Nerkar, 2001; Sorenson & Fleming, 2004; Stuart & Podolny, 1996).

Knowledge recombination strategies have been the object of mounting literature origins from firms' sourcing and processing activity(Hagedoorn & Schakenraad, 1994; Leone et al., 2022; Nerkar & Miceli, 2016; Nicholls-Nixon & Woo, 2003). After acquiring external new information, recombine it with the original knowledge base into new form outputs, improving internal knowledge resource structure and reducing innovation cost(Urgal et al., 2013), with the result of continually upgrading their technical skills and product.

Tacit knowledge is the core of long-term success in the high-tech sector (Christensen, 2013; Kogut & Zander, 1992; Nerkar & Roberts, 2004; Nicholls-Nixon & Woo, 2003), such as patent-intensive (PI) firms. PI firms aim to achieve breakthrough innovation and disruptive innovation that requires intelligent sensing and efficient utilizing mechanism for tacit knowledge. The boundary-spanning strategy and tacit knowledge recombination make it a valuable capability for companies to gain a competitive advantage (Spender, 1993). However, less attention has been paid to tacit knowledge's access and recombination mechanism. The knowledge an organization handles is not limited to that created internally through research and development, learning by doing and utilizing, and formal and informal contact among employees, specially reserved for professional staff(Brown & Duguid, 1991; Nonaka & Toyama, 2015). Such tacit knowledge can flow into the communication and cooperation among entities, mainly in R&D collaboration(Bogers, 2011).

The *network theory* (Baptista & Swann, 1998; Maillat, 1995) proposed the collaborative knowledge relationship as an essential channel to raw materials for innovative activity, in which flowing tacit knowledge spillovers. In light of that, identifying, acquiring, and utilizing tacit knowledge resources are particularly important through co-innovation, such as joint-patent networks. The ability to obtain and utilize intangible intellectual capital depends on the different position advantages of the network. With the dynamic network position, how to ensure the operation of joint-patent networks to achieve a balance between exploitative (local) and explorative (distant) search behaviour (Cohen & Levinthal, 1990) allows firms to optimize the maximum effect of tacit knowledge recombination has aroused the attention of scholars(Y. Wang et al., 2012; Wójcik, 2015). However, the existing literature does not discuss how strategic boundary-spanning and tacit knowledge recombination mechanisms promote technological innovation.

This paper will apply data envelopment analysis (DEA) and social network analysis (SNA) methods to evaluate technological innovation performance and the position advantage of co-innovation. In this regard, the paper aims to explore how to make a boundary-spanning strategy via tacit knowledge recombination from the co-innovation perspective. VisualizationData analysis is visualized. Before concluding, there is a discussion of theoretical and practical implications.

This paper is constructed as follows. Firstly, it clarifies the concept of China's PI firms, which rely on tacit knowledge as raw materials to innovate constantly. At the same time, 103 sample firms fall into the criteria that own more than 500 invention patents and constantly conduct R&D activities for five years. After setting the sample, we apply the BCC output-oriented variable returns to scale the DEA model to calculate the technological innovation performance of those 103 PI enterprises. According to the results, violin charts are drawn by R ggplot2 from the industry view, and each industry's technical innovation performance will be analyzed deeply. Then, to build joint-patent networks of 103 PI firms, the SNA method is adopted, and the index of the network structure is calculated by years. After that, we embed network characteristics indicators of each industry into the industry technological innovation performance for in-depth observation of different operation patterns varies from PI industries. For better theoretically justifying the relevance of the data results and the practical contributions, the R graph draws the topological ego-networks structure of representative firms in every industry, providing illustrative case examples to support strategic boundary spanning through tacit knowledge recombination benefiting PI technological innovation.

This paper analyses the joint-patent networks from the enterprise and industry perspective and studies the joint-patent network's embeddedness and technological innovation performance. We hope to bring new ideas for technology innovation research through an in-depth study of patent-intensive enterprise, sharing and flow of tacit knowledge resources and joint-patent networks.

2. Literature review and theory development

2.1 Patent-intensive firms and tacit knowledge

With the release of the report *Intellectual Property and the US Economy: Industries in Focus* (ESA, 2012), the concepts of "patent density" and "patent-intensive industries" has gradually entered the vision of scholars. From the perspective of research content, two main issues are concerned: first, the definition of "patent-intensive". Scholars and policymakers have been updating the definition and criteria of "patent-intensity" and refining the scope of PI industries, taking into account the actual situation of local technological innovation(de Rassenfosse & van Pottelsberghe de la Potterie, 2013); secondly, the research on innovation management regards the value orientation of patent-intensity(Lv et al., 2018).

It is worth noting that PI enterprises are different from technology-intensive enterprises. Technology-intensive enterprises emphasize their reliance on highly sophisticated technologies. PI enterprises emphasize the high knowledge density and that the production and operation sectors they are engaged in are oriented toward developing national innovation. Technology-intensive enterprises, on the other hand, are those with a relatively high degree of technological equipment, requiring a relatively small number of labourers or manual operators, and with a large share of production costs consumed by technological content. In contrast, PI enterprises cover a broader range.

As the knowledge ecosystem's basic unit, PI firms rely heavily on knowledge resources to drive innovation and gain a competitive advantage. They use patents as their most critical intellectual asset to gain a competitive advantage. Tacit knowledge, embedded in an individual's experience, skills, and expertise, is a core resource for these firms(Mohajan, 2016). It is not easy to codify and transfer this knowledge, making it a valuable asset for the firm. For example, an engineer with years of experience working on a specific product may intuitively understand technical challenges that cannot be written down or communicated to others.

The key to fostering a lasting competitive advantage for PI firms is effectively managing the value chain of knowledge assets and increasing the added value of internal and external knowledge resource(Pickering & Matthews, 2000). Lee argues that PI industries exhibit high vertical integration(P. Lee, 2019). This is due to the difficulty of transferring patent-related "tacit knowledge," which reduces independent innovators and increases market entry barriers(P. Lee, 2019). Cumming and Leung found that in high-tech, especially PI industries, scientific experience and expertise are more important than gender diversity type, and boards with technical backgrounds can better leverage R&D expenditures to create higher value(Cumming & Leung, 2021).

Recently, researchers have started to discuss the innovation or other performance of PI firms. Malerba and McKelvey propose a new concept of entrepreneurship in PI firms based on the integration of entrepreneurship, evolutionary economics, and innovation systems approaches: entrepreneurs in PI firms are involved in knowledge creation, dissemination, and use; introduce new products and technologies; draw resources and ideas from their innovation systems; and introduce change and dynamism into the economy(Malerba & McKelvey, 2020). Naeini investigated the dynamic capabilities that influence the business models of PI firms. The study showed that management capabilities, innovation capabilities, intellectual capital, information technology, integration capabilities, and knowledge-based capabilities influence the business models of PI firms(Bonyadi Naeini & Jalilian Ahmadkalaei, 2021).

By managing tacit knowledge effectively, patent-intensive firms can improve innovation performance and reduce innovation costs. They can gain a competitive advantage by leveraging their employees' knowledge and expertise and developing new products and processes protected by patents.

2.2 Boundary spanning and knowledge recombination

Knowledge management systems are only functional if the link between knowledge management and organizational strategy is revealed(Tiwana, 2000), which undoubtedly confirms the importance of the integration and evolution of knowledge management and strategic management. Trivedi and Srivastava's research emphasizes the importance of aligning knowledge management objectives with the overall strategic goals of a company(Trivedi & Srivastava, 2022). For PI firm's technological innovation goal, the strategy dichotomizes into *boundary spanning* versus *knowledge recombination*(Leone et al., 2022).

Based on a widely recognized research argument(Fischer et al., 2021), efficient knowledge management methods are crucial for patent-intensive entrepreneurial enterprises' success. Knowledge management can moderate the relationship between technological knowledge and company performance. Bismo also found that knowledge management strategies affect firm innovation and performance(Bismo et al., 2021). Researchers suggest that efficient knowledge strategies are crucial for the success of PI enterprises(Yoshikuni et al., 2022;Tajpour et al., 2022).

Meanwhile, PI firms shall set store by strategical management of intangible intellectual capital via exploring and utilizing employees' abilities, experience, and expertise; organizations may build a dynamic and adaptable workplace that fosters creativity and problem-solving. For example, the experience and expertise of individuals within the firm can lead to innovations, insights, and solutions that can be patented and commercialized (Schneckenberg et al., 2015). This process involves both technology boundary spanning and tacit knowledge recombination. Identifying and acquiring tacit knowledge resources flowing in knowledge spillover is challenging(Pérez-Luño et al., 2019).

Combining boundary-spanning and knowledge recombination concepts can help patent-intensive (PI) firms achieve their technological innovation goals. Networking and collaboration through boundary-spanning activities facilitate the acquisition of new knowledge and the integrating of diverse expertise. In contrast, knowledge recombination processes can lead to new knowledge that is not merely replicating what already exists. In the context of PI firms, joint-patent networks can facilitate tacit knowledge recombination, which can be a critical mechanism for improving technological innovation performance and competitiveness(Trivedi & Srivastava, 2022). Efficient knowledge management strategies are also essential to support boundary spanning and knowledge recombination, and aligning knowledge management objectives with overall strategic goals can lead to better performance outcomes(Trivedi & Srivastava, 2022).

Furthermore, PI firms should prioritize the strategic management of intangible intellectual capital and leverage their employees' abilities, experience, and expertise to build a dynamic and adaptable workplace that fosters creativity and problem-solving. By combining boundary spanning and knowledge recombination, PI firms can create new knowledge and innovative solutions that can help them gain a competitive advantage in the market. Efficient knowledge strategies are crucial for the success of PI enterprises, as they can moderate the relationship between technological knowledge and company performance(Bismo et al., 2021; Tajpour et al., 2022; Yoshikuni et al., 2022). Therefore, integrating knowledge management and strategic management can facilitate the alignment of knowledge management objectives with overall strategic goals, providing PI firms with a valuable framework for improving technological innovation performance and competitiveness.

2.3 Joint-patent networks and knowledge-creating alliances

A joint-patent network is a group of organizations connected through a shared research project(Reypens et al., 2016), resulting in technological outputs in the form of shared patent rights. By participating in innovation networks, enterprises can access tacit knowledge in the expert brain, reflecting on behaviours and ideas that can help to drive innovation and improve performance(Parida et al., 2012). In joint-patent networks, the flow and transformation of tacit knowledge resources are affected by many factors. The network position of a company is relevant for identifying, acquiring and recombining tacit knowledge through innovation networks(Fritsch & Kauffeld-Monz, 2010; Ganguly et al., 2019).

With technological innovation's increasing complexity and uncertainty, the traditional innovation model is bound by limited and unitary knowledge resources, which cannot meet the requirements of open innovation or breakthrough innovation. With the deepening of R&D cooperation and interaction, firms' technological innovating pattern gradually develops from a linear to a network model(Liu et al., 2020).

Collaborative knowledge relationships can involve face-to-face meetings, brainstorming sessions, or informal conversations between individuals directly from different entities(Treasure-Jones et al., 2019). Individuals can learn new skills, techniques, and ideas from collaborators, which can then be incorporated into an organization's knowledge base. Joint-patent networks of patent-intensive enterprises are collaborative networks in which organizations share resources, knowledge, and expertise to develop innovative products and services. Chesbrough and Bogers argue that collaborative R&D networks can be valuable tools for open innovation and knowledge creation(Chesbrough & Bogers, 2014). The authors suggest that tacit knowledge plays a critical role in joint-patent networks. It enables partners to develop a shared understanding of problems and solutions and engage in collaborative problem-solving. They note that successful joint-patent networks require the creation of trust and social capital among partners, which the sharing of tacit knowledge can facilitate.

A key component of successful joint-patent networks is sharing tacit knowledge among *knowledge-creating alliances* (Romero & Molina, 2011). Knowledge-creating alliances involve sharing both explicit and tacit knowledge between partners. Sharing explicit knowledge, such as technical specifications and patents, is essential for developing new products and services. Narula and Hagedoorn argue that explicit knowledge can be transferred relatively quickly, and it is essential for firms to manage and protect it effectively(Narula & Hagedoorn, 1999). However, the sharing of tacit knowledge is more challenging as it involves the transfer of knowledge that is difficult to codify, such as skills, experiences, and intuition. Nonaka and Takeuchi suggest that tacit knowledge is the most critical resource for knowledge creation, and it plays a crucial role in developing new products and services(Nonaka & Takeuchi, 1995).

Combining joint-patent networks and knowledge-creating alliances can create a collaborative innovation ecosystem that leverages the strengths of both approaches. Chesbrough and Bogers suggest that successful joint-patent networks require the creation of trust and social capital among partners, which can be facilitated by sharing tacit knowledge(Chesbrough & Bogers, 2014). In this ecosystem, firms can access diverse knowledge resources from their network partners and collaborate more effectively with their knowledge-creating alliance partners. Liu et al. argue that this ecosystem can enable firms to develop innovative products and services that meet the market's changing needs (Liu et al., 2020).

Thus, combining joint-patent networks and knowledge-creating alliances can create a powerful mechanism for driving innovation and improving performance. By sharing explicit and tacit knowledge, firms can access a diverse range of knowledge resources, collaborate more effectively, and develop innovative products and services that meet the market's changing needs. This collaborative innovation ecosystem requires the creation of trust and social capital among partners, which can be facilitated by sharing tacit knowledge.

3. Research methodology

3.1 Methodology

Firm's technological innovation performance

Academic research on measuring a firm's technological innovation performance can be classified into three categories: single-indicator measures, multiple-indicator measures, and questionnaires. Although the questionnaire method is widely used, it only provides cross-sectional data. It needs to capture changes in technological innovation performance, which makes it inappropriate for this paper's model setting. Single-indicator measures, such as the number of patent applications or grants, are commonly used as proxy indicators for technological innovation performance. However, these measures have several limitations, including a long time lag and being influenced by patent offices and policies.

The choice of data envelopment analysis(DEA) method for measuring technological innovation performance in patent-intensive enterprises is supported by its ability to decompose TFP and accommodate technological heterogeneity. The approach has been extensively utilized to assess effectiveness. (Çelen, 2013; M.-H. Chen et al., 2018; Zhang et al., 2020). While parametric methods like OP, LP, and structural equations accurately measure TFP, they have limitations in subsequent regression analysis and cannot separate TFP from technological innovation performance. On the other hand, DEA measures innovation performance from input-output data, does not require a production function, and accommodates technological heterogeneity(Liang et al., 2020). Although DEA has limitations in accounting for random errors and unknown production processes, it is suitable for the research scenario of this paper focuses on knowledge management strategy in patent-intensive enterprises.

DEA is rooted in the concept of efficiency, a fundamental concept in economics. The method seeks to measure the relative efficiency of decision-making units (DMUs), which in the case of this study, are patent-intensive enterprises. Innovation performance is a form of efficiency in that it measures the ability of an enterprise to produce new and valuable outputs from a given set of inputs. By using DEA to measure innovation performance, this study is essentially measuring the efficiency of innovation, which is a crucial factor in the success of patent-intensive enterprises. Despite differing definitions of 'performance' by scholars, they all agree that performance is a relationship between 'output outcomes' and 'inputs.' For example, Kraus defines performance measurement as 'output characteristics for goal assessment'(Kraus, 1984), Fortuin as a means of measuring the gap between actual outcomes and input goals(Fortuin, 1988), and Kagioglou as the degree to which goals are achieved(Kagioglou et al., 2001). While single indicators only reflect a firm's innovation output, multi-indicators provide a more comprehensive view of technological innovation performance.

That is another theoretical advantage of the DEA method. It allows for the inclusion of multiple inputs and outputs in the analysis. This is important in measuring innovation performance, as innovation is often the result of a complex interaction between multiple factors(Guan et al., 2006), such as R&D investment, human capital, and the ability to collaborate with external partners. By including multiple inputs and outputs in the analysis, DEA is able to capture this complexity and provide a more comprehensive measure of innovation performance.

Since the DEA approach was proposed by Charnes et al.(Charnes et al., 1978), scholars have continuously developed and refined various models based on the DEA, among which CCR, BCC, and other models are commonly used to evaluate technical efficiency (Pastor & Lovell, 2005). Assuming constant payoffs to scale in the CCR model, the efficiency evaluation index of the j-th decision-making unit (DMU) is θ_j:

$min\vartheta_j$

$$\sum_{i=1}^{m}\lambda_j x_{ij} \leq \vartheta_j x_0, \quad i = 1,2,\cdots,m$$

$s.t.$

$$\sum_{r=1}^{s}\lambda_j y_{rj} \geq y_0, \quad r = 1,2,\cdots,s$$

$$j = 1,2,\cdots,n$$

$\lambda_j \geq 0$

ϑ_j is the efficiency; firms with solution $\theta_j = 1$ are regarded as relatively efficient or benchmark firms. Their performance determines the efficient frontier, while firms for which $\theta_j < 1$ are regarded as inefficient.

$x_{ij} = (x_{1j}, x_{2j}, \cdots, x_{mj}) > 0$ is inputs.

$y_{rj} = (y_{1j}, y_{2j}, \cdots, y_{sj}) > 0$ is outputs.

λ_j is the intensity factor means the contribution of firm j in the derivation of the efficiency of another firm.

In addition, we utilized the window-DEA method to account for time effects, i.e. to conduct horizontal comparisons between decision-making units (DMUs) and historical comparisons of the same DMU(Flokou et al., 2017; Stefko et al., 2018). According to previous research, the window period for this study is three to four years (Cullinane et al., 2004; Fadzlan & Muhd-Zulkhibri, 2007; Hemmasi et al., 2011).

Assuming j DMUs, t data periods, and a d time window width, each DMU has $t - d + 1$ time windows and d efficiency values in the $f(f = 1,2, cdots, t - d + 1)$ time window. The input-oriented calculation formula for each DMU at the $e(e = 1,2, cdots, d)$ time point within the $f(f = 1,2, cdots, t - d + 1)$ time window is shown below.

$(D)min\vartheta_j$

$$\sum_{i=1}^{d\times m} \lambda_j^{fe} x_{ij}^{fe} \leq \vartheta_j^{fe} x_0^{fe}, \quad i = 1,2,\cdots,m$$

$s.t.$

$$\sum_{r=1}^{d\times s} \lambda_j^{fe} y_{rj}^{fe} \geq y_0^{fe}, \quad r = 1,2,\cdots,s$$

$$j = 1,2,\cdots,n$$

$\lambda_j \geq 0$

x_0^{fe} is the ith input of the jth DMU at the eth time point within the fth window.

y_0^{fe} is the rth output of the jth DMU at the eth time point within the fth window.

ϑ_j^{fe} is the optimal solution of the above model.

Joint-patent networks

This paper uses complex network and social network theories(Wasserman & Faust, 1994) to construct an enterprise joint-patent networks based on data from enterprises' joint application for invention patents, analyzes its topology, measures the relevant indicators of the enterprise joint-patent networks, and analyzes the evolution of the dynamic development of the enterprise joint-patent networks to establish a decision basis for joint R&D of China's PI industries.

Based on the social network analysis method, this paper uses the R graph package to construct the topology diagram of the overall network and the egocentric network of the joint-patent networks and calculate the relevant indicators for analysis. The specific steps are as follows.

First, the R dplyr package is applied to collate the data and construct the cooperation matrix of the patentees in five time periods. The cooperation matrix represents a one-to-one correspondence between patentees, i.e. the co-innovation between patentees. The collaboration matrix for each year can be represented as follows:

$$G = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ g_{i1} & G_{i2} & \cdots & g_{in} \end{bmatrix}$$

where $g_{in}(i = 1,\ 2,\ i;\ n = 1,\ 2,\ n)$ is the number of joint patent applications for the i-th organization and the n-th organization.

The collaboration matrices were then transformed into adjacency matrices using the graph package in R for five years, resulting in five adjacency matrices. The topology of the joint-patent networks was visualized using these adjacency matrices, where points and collaborative relationships represented the patentees were depicted by lines. Subsequently, various network indexes of the joint-patent networks were calculated, including network size, the number of lines, network density, transitivity, network means path and network centrality. The structural hole degree and co-innovation depth were determined for the ego network of the joint-patent networks. The ego network of some patent-intensive enterprises was visualized to explore the structural evolution of the joint-patent networks. The indicators' meanings were as follows: network size represented the number of nodes in direct contact with the central node, including the central node; the number of lines referred to the total number of connections between nodes in the joint-patent networks; and network centrality denoted the degree to which knowledge collaboration is concentrated in one or a few core nodes carrying out network activities. Network density is the ratio of the total number of ties in the network to the maximum number of relations that could exist. It measures the closeness of connections between individual nodes of the network.

The network clustering coefficient is the average of the clustering coefficients of all nodes, which reflects the clustering of the joint-patent networks. The formula(Barrat et al., 2004)is as follows, s_i is the strength of vertex i, a_{ij} is the elements of the adjacency matrix, k_i is the vertex de degree, and w_{ij} is the weight.

$$C_i^w = \frac{1}{s_i(k_i-1)} \sum_{j,h} \frac{w_{ij}+wih}{2} a_{ij}\, a_{ih} a_{jh}$$

Cooperation depth: Most scholars use the average number of cooperation times to measure the depth of cooperation(Yan et al., 2019). In this paper, we consider that in social networks, if a node is at the network's core, it will have a significant influence even if the degree is small. In contrast, large degree nodes at the edges often have limited influence. Therefore, Kitsak et al. propose a method for determining the location of nodes in a network using k-core decomposition (k-shell, also called k-core decomposition), which recursively strips away the peripheral nodes layer by layer until the nodes are indistinguishable(Kitsak et al., 2010).

Empowerment Level: Burt's constraint refers to how an individual's network of contacts restricts the flow of information and resources. This constraint is increased when the individual has fewer or more closely related contacts in their ego network. Higher constraints indicate more significant limitations on access to novel information and diverse perspectives(Burt, 2004). Burt's measure of constraint: C_i is the constraint for the firm i's ego network, j is another organization, and q is the third organization. p_{ij} is the proportional strength of the relationship between focal firm i and j. a_ir is an element in the adjacency matrix A.

$$C_i = \sum_{j \in V_i \setminus \{i\}} \left(p_{ij} + \sum_{q \in V_i \setminus \{i,j\}} p_{iq}\, p_{qj}\right)^2$$

$$p_{ij} = \frac{a_{ij}+a_{ji}}{\sum_{k \in V_i \setminus \{i\}} (a_{ik}+a_{ki})}$$

This measure reflects the degree to which the focal vertex's connections are necessary to maintain the flow of information in the network. It thus provides insight into an individual's role in the network's overall structure and function.

3.2 Data

In the DEA model, multiple input and output factors are included to determine the efficiency of each DMU. We use R&D personnel and R&D capital as input variables(Hall et al., 2010; E. C. Wang, 2007). The number of patents granted and new product sales revenue are used as output variables(Elia et al., 2019).

Patent grants and new product sales revenue are considered output variables of each DMU in the DEA model. Because R&D inputs cannot typically produce outputs within one year, we use patent grants rather than patent applications to reflect the time lag. In addition, because the new product sales revenue on the firm level was unavailable, it was calculated using the industry's average new product sales revenue multiplied by the firms' ROA (Sofka & Grimpe, 2010). The industry data are collected from *China Industrial Statistics Yearbook* and *China Science and Technology Statistics Yearbook*. To ensure the accuracy of the sample selection, this study treats the absence of information on relevant indicators of individual high-tech enterprises as missing values and excludes them from the analysis.

Moreover, to mitigate the impact of outliers, the data of the variables are truncated at the 1% and 99% tails, respectively. Some firms have a zero value for the number of patents granted in specific years, which the DEA model does not accept. A small value of 0.0001 is used instead of zero to address this issue, following the precedent set by other researchers(Bowlin, 1998). The calculation of R&D capital as an input variable follows the method proposed by Hall and Lerner(Hall & Lerner, 2010). Additionally, we include the full-time equivalent of R&D personnel to measure another input variable, R&D personnel(Baumann & Kritikos, 2016).

This study focuses on Chinese-listed companies operating in patent-intensive industries. To identify the initial sample, we employed the Patent-Intensive Industry Catalogue (2016) and the SFC Industry Classification Standard (2011)(Chang et al., 2022). As the Patent-Intensive Industry Catalogue (2016) uses three-digit industry codes, and the SFC Industry Classification Standard 2011 utilizes two-digit industry codes, the initial sample was chosen to include only those industries in which the first two digits of the three-digit industry codes of the Patent Intensive Industry Catalogue (2016) matched the industry classification codes of listed companies. We further screened the listed companies to ensure that the initial sample consisted only of patent-intensive industries. We selected those with more than 500 patents, resulting in a sample of 103 listed companies. One invention patent was selected from the State Intellectual Property Office for each listed company to obtain information about the patentees. We then retrieved the name of the listed company in the Derwent Innovations Index (DII) and the standard code of the patentee based on the patent number. This was done because the DII provides a unique standard code for each patentee, which covers all branches of the patentee's patent applications. In contrast, the State Intellectual Property Office database does not allow for this type of correspondence. We performed a final search for all patents from 2015 to 2019 using the names and standard assignee codes obtained from all DII-listed companies, resulting in a total of 113,892 patents.

Drawing on social network theory, the present study constructs socio-centric and egocentric networks for publicly traded companies operating in patent-intensive industries. The socio-centric network characteristics describe co-innovation(Saadatyar et al., 2020). In contrast, the structural features of egocentric networks are examined to determine the impact of such characteristics on technological innovation performance. 103 companies and 113,892 patents from 2015 to 2019 are analyzed, following the exclusion of patents from single patent owners, joint patentees with individuals, and joint patentees that involve parent and subsidiary companies (excluding equity alliances). Patents that involve collaborations between publicly traded companies and organizations represented by universities, research institutions, and DII non-standard patent owner codes are also included in this study(Yuan & Li, 2020). Using this data, 563 R&D organizations are identified and used to construct socio-centric network structures, and the relevant indicators for the egocentric network of 103 patent-intensive listed companies are calculated. To augment this data, the China Research Data Service Platform (CNRD) database provides information on R&D investment and patents, while the Resset database offers companies' financial and market data. In order to minimize sampling errors, this study treats the non-disclosure of relevant indicators of individual high-tech enterprises as missing values, which are removed. Furthermore, data variables are subjected to 1% and 99% tail reduction to eliminate outliers.

4. Result and discussion

4.1 The technological innovation performance of patent-intensive listed firms

According to Figure 1， our analysis reveals that the end of the innovation performance of local patent-intensive firms is declining, suggesting that these firms prioritize technological innovation and are continually striving to catch up with the latest developments(J. Chen et al., 2011). Specifically, the end of the violin plot shifts from a long teardrop shape to a tapered shape, indicating not only an upward trend in the lowest value of patent-intensive enterprises over time but also the existence of a bottleneck period for technological catch-up in the years 2017 and 2018, during which many low-performing firms completed their technological efficiency improvement efforts(Deng & Lu, 2022; K. Lee, 2005; H. Yang & Zhu, 2022). The tightening of the violin belly arc trend implies that the polarization of technical efficiency of patent-intensive enterprises in China has been alleviated, pointing to an overall upward development trend(Kumar & Sundarraj, 2018).

Using the R ggplot two packages to construct a violin plot and exploring the distribution and trends in the innovation performance of the sample firms over time from the perspective of industry heterogeneity (see Figure 1). The higher technological innovation performance of patent-intensive firms across all industries is attributed to their focus on technology and knowledge as core competitive resources, rendering them innovation agents and industry leaders in technological innovation(Gertler & Levitte, 2005; Kurzhals et al., 2020). However, the technological innovation efficiency of patent-intensive firms varies across industries, particularly in computer, communication, and other electronic equipment manufacturing sectors, where firms face a significant polarization issue(Yan et al., 2021). Although the number of firms in the middle and upper reaches of the industry is comparable to the number of technologically efficient firms, those at the tail end exhibit low technological innovation efficiency. In such a knowledge ecological environment, there are more tacit knowledge gaps, which innovation agents can optimize through innovation relationships with partners to leverage tacit knowledge resources(Grant, 1996; Kogut, 1988).

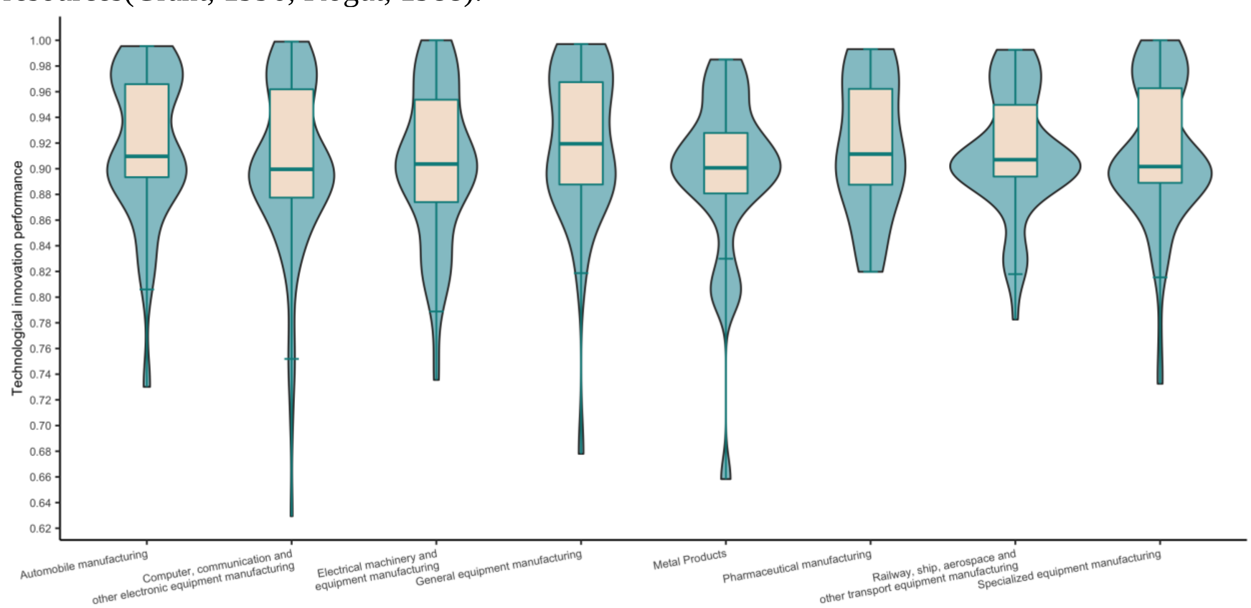

Figure 1 Differences in technological innovation performance by industry

The technical efficiency of patent-intensive firms in the pharmaceutical manufacturing industry and the railway, ship, aerospace, and other transport equipment manufacturing industry has developed evenly and is less polarised than in other industries. The violin plot illustrates that the ends of the violins for these two industries are tapered, indicating that the lowest values of innovation performance have trended upward over the years. In contrast to the computer, communication, and other electronic equipment manufacturing industries where the violin ends are still teardrop-shaped, the more uniform shape of the violin ends in the pharmaceutical manufacturing and transport equipment manufacturing industries implies less polarization of innovation performance among the firms.

Taking into account the presence of tacit knowledge gaps in the computer, communication, and other electronic equipment manufacturing industries(Venkitachalam & Busch, 2012), it is worth noting that the optimization of innovation relationships with partners can help patent-intensive firms tap into tacit knowledge resources to improve their technological innovation efficiency(Tamer Cavusgil et al., 2003). However, the even distribution of technical efficiency of patent-intensive firms in the pharmaceutical manufacturing industry and the railway, ship, aerospace, and other transport equipment manufacturing industries suggests that these industries may have a less pronounced tacit knowledge gap. For instance, in the pharmaceutical manufacturing industry, patent-intensive firms may rely on direct technology transactions, such as patent licensing and the purchase of related instruments, which are explicit rather than tacit knowledge(Silverman, 2018). Similarly, in the railway, ship, aerospace, and other transport equipment manufacturing industries, patent-intensive firms may leverage close relationships with suppliers and customers to gain insights into emerging technologies and market demands(David et al., 2018).

Based on the analysis of the patent-intensive enterprises' innovation performance across various industries, the role of tacit knowledge in influencing technological innovation can be examined. In industries such as computer, communication, and other electronic equipment manufacturing, the technological innovation efficiency of enterprises in the tail is too low, indicating the presence of more tacit knowledge gaps. However, in the pharmaceutical manufacturing industry and the railway, ship, aerospace, and other transport equipment manufacturing industries, the technical efficiency of patent-intensive firms has developed evenly and is less polarized. This may be due to the nature of these industries, which tend to have more explicit knowledge that can be codified and shared among industry players. Innovation agents can optimize their innovation relationships with partners to tap into tacit knowledge resources in such a knowledge ecosystem.

Overall, these findings suggest that the distribution and polarization of technical efficiency of patent-intensive firms are heavily influenced by industry-specific characteristics, including the prevalence of tacit knowledge and the availability of effective channels for leveraging it(Cassiman & Veugelers, 2006). In industries where tacit knowledge is abundant and difficult to codify, patent-intensive firms may need to adopt more collaborative approaches to innovation to remain competitive(P. Lee, 2018).

According to our analysis of the technological innovation performance of eight industries over five years (see Figure 2), we found that in 2015-2016, the innovation efficiency of patent-intensive enterprises in each industry was concentrated in the upper end of the spectrum but a polarizing trend emerged in 2017-2018, which was somewhat alleviated in 2019. This trend is particularly evident in the metal manufacturing industry, where the technical efficiency of patent-intensive enterprises demonstrated an overall downward trend(X. Wang et al., 2021).

Furthermore, the technical efficiency of patent-intensive enterprises in pharmaceutical manufacturing, previously high, has shown a slowing trend in recent years, and the technical efficiency of patent-intensive enterprises in automobile manufacturing has gradually widened the gap.

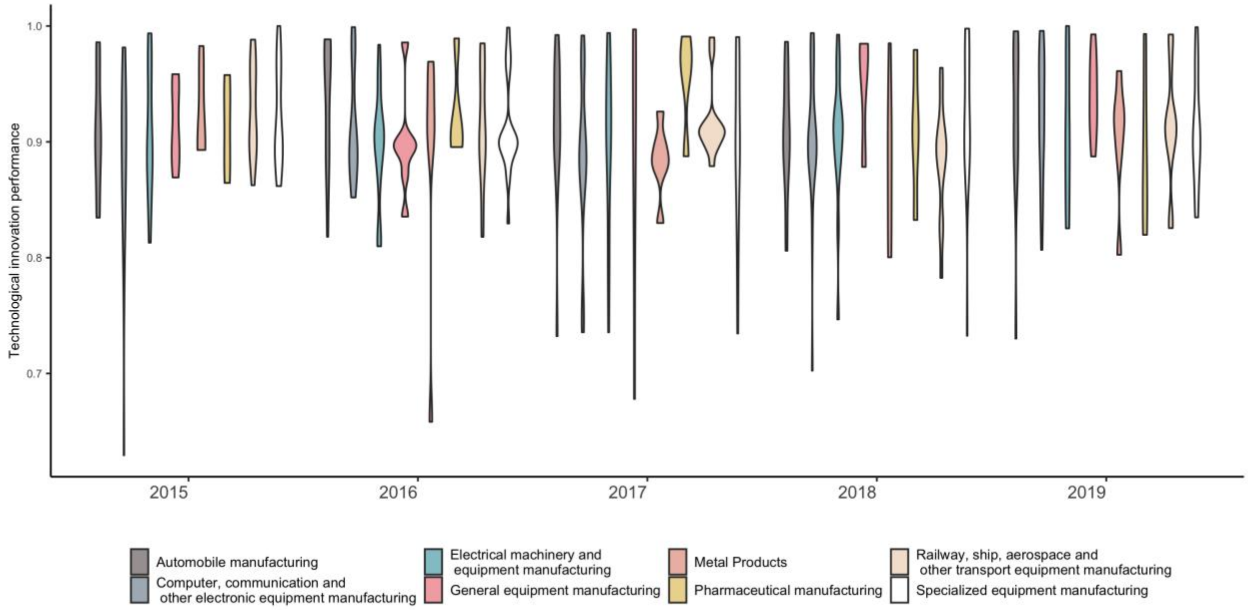

Figure 2 Industry trend analysis

These findings highlight that while the top performers in each industry generally remain stable, most enterprises' technical efficiency varies greatly, leading to the possibility of polarization in innovation efficiency. Schultz found that the share of US funding invested in patent-intensive startups has declined, falling from over 50% in 2004 to about 28% in 2017, with less patent-intensive industries attracting significant venture capital(Schultz, 2020). To achieve innovation-led sustainable economic development, patent-intensive enterprises must maintain a steady increase in technical efficiency and narrow the industry's relative level. To achieve this, innovation players must make a knowledge recombination strategy to maximize the utility of their knowledge resources and improve innovation performance based on their knowledge resource levels and the industry's knowledge resource environment(Y. Yang et al., 2022).

4.2 Joint-patent networks

4.2.1 The whole network analysis

In this paper, we use a graph to map the five-year joint-patent networks and calculate the individual indicators of the five-year network characteristics, as detailed in Table 1.

Table 1 Overall Indicators for the joint-patent Networks 2015-2019

	2015	2016	2017	2018	2019
Size	532	500	563	334	371
Edge	773	2770	3612	1820	2324
Density	0.005	0.022	0.023	0.033	0.034
Clustering coefficient	0.647	0.585	0.529	0.543	0.537
Diameter	3.901	3.836	3.555	3.223	3.093

Centrality	0.145	0.896	1.465	2.093	2.723

According to the findings presented in Table 1, there are two main observations regarding joint-patent networks involving patent-intensive enterprises. Firstly, these networks' size and number of lines have changed over the observation period. The size of the networks decreased from 532 in 2015 to 371 in 2019, indicating that more organizations left the collaborative networks. However, the number of lines increased from 773 in 2015 to 2,324 in 2019, representing a three-times increase. This suggests that even though more organizations left the network, the remaining incumbents increased their collaboration efforts, leading to increased stability and frequent knowledge exchange within the collaboration network.

Secondly, core nodes within the joint-patent networks have become increasingly important. Network centrality, as a measure of the importance of individual nodes within a network(Aadithya et al., 2010), increased from 0.145 in 2015 to 2.723 in 2019, implying that some nodes in the network have become core nodes. This suggests that joint-patent networks involving patent-intensive enterprises have a core-periphery structure, where a small group of nodes plays a critical role in the network's knowledge exchange and innovation outcomes.

Thirdly, the joint-patent networks of patent-intensive enterprises are lower. Among them, the network density of 5 years is between 0.005-0.034, the network connection is not close, and the clustering coefficient is declining; the network as a whole tends to be loose. This may be due to an increase in the number of quitters. At present, networks have a low density and their functions need to be improved. There is considerable space for developing joint-patent networks, and organizations can further leverage their strengths to build more extensive and in-depth co-innovation with other actors.

Furthermore, the joint-patent networks where patent-intensive enterprises participate initially exhibit small-world characteristics. Valverde et al. defined small-worldness as a network with an average distance of less than ten and a clustering coefficient greater than 0.1(Valverde et al., 2002). However, the above criteria could be relaxed appropriately for large network sizes. The five-year joint-patent network's clustering coefficients are all greater than 0.5, indicating that the network is sparsely connected and information transferability is low. Second, the average path length of the 5-year joint-patent networks ranged between 3-4, indicating that network nodes needed to pass through 3-4 intermediaries to establish connections on average.

Thus, the joint-patent networks in which patent-intensive enterprises participate in China exhibit a small-world effect overall. Innovation organizations can establish cooperation with other organizations more efficiently and draw in heterogeneous knowledge from outside, which promotes the level of cooperative patent R & D output.

4.2.2 Embedding analysis of technology innovation performance and joint-patent networks

Several studies have explored the relationship between inter-firm co-innovation, external technology acquisition, and innovation performance. Researchers found that inter-firm co-innovation entails additional transaction costs such as finding and selecting partners, allocating resources, and coordinating and managing R&D activities, ultimately eroding a firm's innovation performance(Fjeldstad et al., 2012). On the other hand, Berchicci (2013) showed that external technology acquisition through co-innovation can enhance innovation performance to some extent, but beyond a certain threshold, it does not(Berchicci, 2013). The firm's knowledge stock influences this threshold effect.

Moreover, scholars have examined the role of structural holes in a firm's innovation performance. Inventors with a higher degree of the structural hole have more timely access to information than other inventors, which aids in the two-way transfer of technology and thus increases the efficiency of technological innovation(Burt, 2004). The structural hole in the network structure serves as a bridge for information transfer, allowing firms to gain information and control advantages that other firms do not have(Burt, 2004). Firms located in the structural hole are actually in the information flow bridge, gathering a large amount of information and resources, which tends to cause information blockage, reducing the use of knowledge(Kontinen & Ojala, 2012).

Furthermore, structural gaps can introduce resource heterogeneity and control into the focal firm. In particular, having a structural hole location gives the focal firm access to diverse resources and knowledge (Burt, 2004). The larger the structural hole position of the focal firm in the network of individuals, the more control it has and the more difficult it is for other organizations to replace it(Vasudeva et al., 2013). Power imbalances between the focal firm and other firms can result from structural hole positions, while other firms and organizations rely on the focal firm(Ahuja, 2000). However, an increase in structural holes can lead to a decrease in the number of technological innovations in a firm(Wen et al., 2021). This is because structural holes imply a need for more connections between network actors, making it difficult for firms to generate corresponding relationships and preventing them from accessing integrated knowledge and resources(Shipilov, 2009). A lack of new knowledge makes it difficult for firms to identify new opportunities for innovation, reducing the number of technological innovations they make(Stuart, 1998).

In this study, we aim to explore the optimal cooperation patterns for enterprises to improve technological innovation performance, considering the heterogeneity of cooperation patterns and technical efficiency in the industries to which the sample enterprises belong. To achieve this objective, we embed the network characteristics indicators of each industry into the industry technological innovation performance network for in-depth analysis.

We employ a graph to calculate each industry's 5-year average depth of cooperation and empowerment level. Then, we calculate the 5-year average value of technological innovation performance in each industry. Finally, we construct a three-dimensional coordinate diagram to observe co-innovation patterns and technological innovation performance embedding. The horizontal axis represents cooperation depth, the vertical axis represents technological innovation performance, and the colour and size of the dots represent empowerment level. We divide the dots into four regions based on the mean value of the overall sample's depth of cooperation and technological innovation performance. We plot the innovation efficiency matrix for each industry using R ggplot2. The matrix visually represents the interplay between cooperation patterns and technological innovation performance for each industry. The colour scheme and size of the matrix allow for easy identification of high and low levels of empowerment. The results are presented in Figure 3.

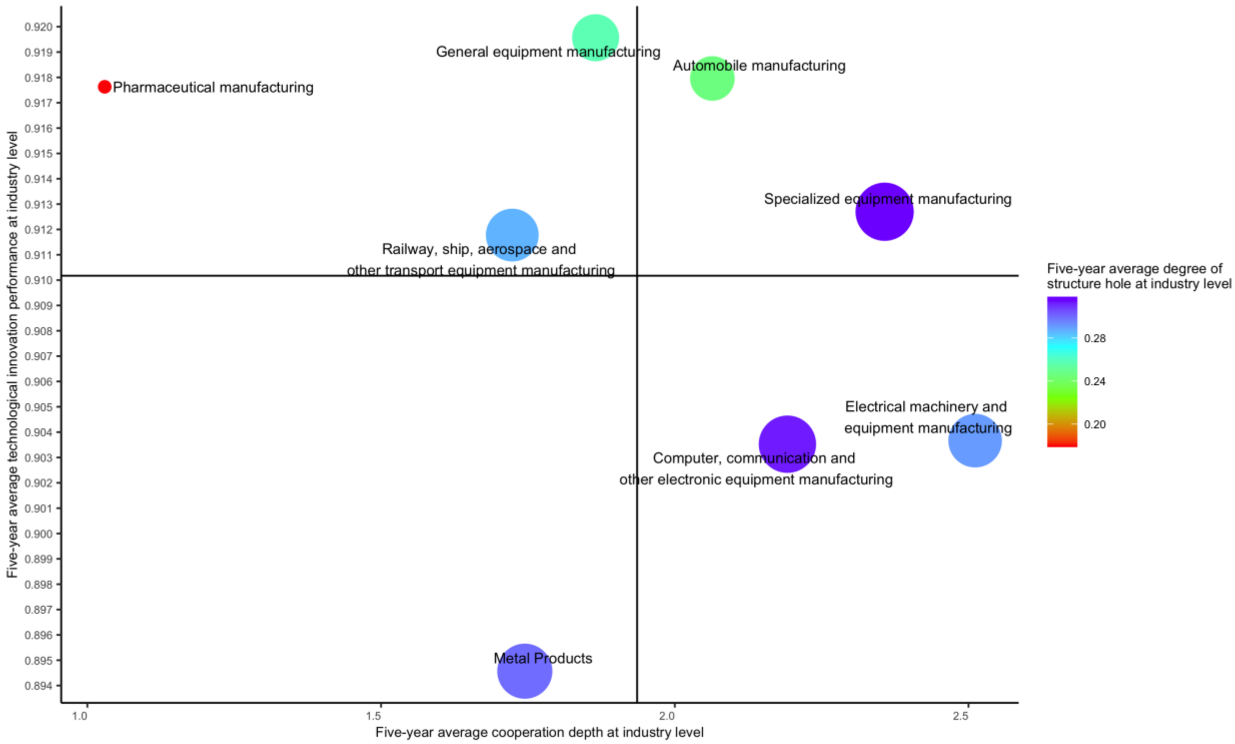

Figure 3 Technological innovation performance classification matrix

Figure 3 presents a visualization of the embedding of co-innovation patterns and technical efficiency across various industries. Notably, the pharmaceutical manufacturing, general equipment manufacturing, and railway, ship, aerospace, and other transport equipment manufacturing industries are depicted as having low levels of cooperation depth but high levels of technological innovation. Among these, pharmaceutical manufacturing exhibits a minor depth of cooperation and empowerment level yet demonstrates excellent technological innovation performance. This suggests that listed pharmaceutical manufacturing companies in China prefer the traditional innovation model, relying on independent R&D rather than collaborative R&D. As a result, the joint-patent networks of the sample companies in this industry are relatively simple, with fewer nodes. This concentration of knowledge resources within the enterprises and lack of flow between them indicates less co-innovation. However, despite the absence of policy incentives, China's pharmaceutical manufacturing industry has displayed high levels of technology innovation performance, as evidenced by various governmental plans and notices(Price, 2014). The industry's reliance on the development of classical remedies with added value rather than compound trials further reduces R&D investment and dependence on external heterogeneous knowledge and technology opportunities, leading to a situation where less co-innovation results in higher technological innovation performance.

On the other hand, while the general equipment manufacturing and railway, ship, aerospace, and other transport equipment manufacturing industries exhibit similar levels of cooperation, their technological innovation performance varies significantly. Moreover, the degree of empowerment level in the general equipment manufacturing industry is less severe than in the railway, ship, aerospace, and other transport equipment manufacturing industries. That implies a negative relationship between empowerment level and technological innovation performance.

In examining the upper right quadrant of the three-dimensional coordinate diagram in Figure 3, it is evident that the automotive and specialized equipment manufacturing industries demonstrate high levels of cooperation depth and technological innovation performance. However, the specialized equipment manufacturing industry exhibits a higher cooperation depth and a greater empowerment level. Nevertheless, its technological innovation performance is significantly lower than that of the automotive manufacturing industry, which has a lower structural hole degree. The automotive industry is based on a single supply chain. In contrast, the intra-industry supply chain of the specialized equipment manufacturing industry is more intricate and presents a more significant number of heterogeneous knowledge and technological opportunities(Fixson & Park, 2008). However, the specialized equipment manufacturing industry also creates a barrier to the flow of knowledge resources, making it challenging for enterprises to assimilate and utilize complex knowledge from the outside world, limiting their potential for future technological innovation(Nonaka & Toyama, 2015). To overcome this hurdle and improve technological innovation performance, patent-intensive enterprises in the specialized equipment manufacturing industry should enhance their knowledge base and take full advantage of the heterogeneous knowledge of high-level empowerment(Whittle & Kogler, 2020). Additionally, they should work towards strengthening mutual trust with their partners to reduce the blockage of knowledge flow caused by high-control enterprises.

Metal manufacturing is the only industry in the lower left region with a low cooperation depth and technological innovation performance. In the patent-intensive industry catalogue, the metal manufacturing industry is classified as intelligent manufacturing equipment(Kusiak, 2018). Unlike the pharmaceutical industry, the metal manufacturing industry is not favoured by policy, resulting in high R&D costs. The metal manufacturing industry generally belongs to the rough and loose innovation mode; the depth of cooperation with partners is shallow, but the flow of knowledge resources is obstructed, and the waste of external knowledge resources is severe(Garriga et al., 2013). It is, therefore, critical that the industry capitalizes on collaborative R&D and that policymakers recognize the metal manufacturing industry's critical role in the intelligent equipment industry and collaborate to improve its R&D and innovation output.

In the lower right-hand area of the diagram, characterized by a high level of cooperation but a low level of technological innovation performance, are two industries: the manufacture of computers and other communications equipment, as well as electronic machinery and equipment. Patent-intensive listed companies in these industries exhibit a high degree of collaboration. However, their technological innovation performance could be better, and the dots' colour and size indicate a high level of empowerment. This indicates that despite fostering mutual trust and gaining access to rich, heterogeneous knowledge from outside the firm, these benefits do not translate into innovation output, and knowledge resources must flow more effectively. Moreover, the higher the empowerment, the more innovation resources are held by individual high-control firms, leading to a decrease in other firms' innovation output and resulting in lower technological innovation performance for the industry.

4.3 The ego network analysis and case study

4.3.1 The ego network analysis

This paper further constructs the co-innovation ego network topology of the patent-intensive listed companies, which rank first in the technology innovation performance of each industry from 2015 to 2019, as shown in Figure 4; when constructing an ego network, the links of duplicated cooperation are removed, in which the more partners, the larger the node size.

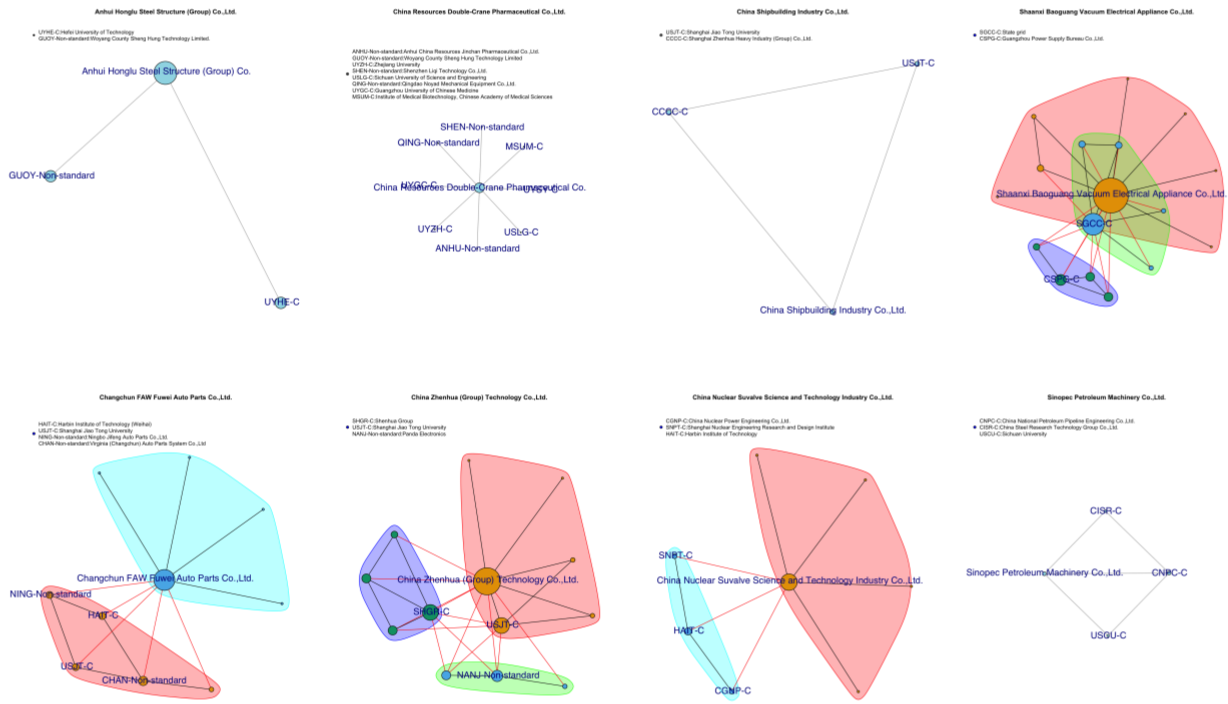

Figure 4 Selected corporate co-innovation ego networks

According to the analysis, certain enterprises exhibit a simple network structure, implying that their innovation mode is mainly independent rather than cooperative. These enterprises include Sinopec Petroleum Machinery Co., Ltd., China Shipbuilding Industry Co., Ltd., Anhui Honglu Steel Structure (Group) Co., Ltd., and China Resources Shuanghe Pharmaceutical Co., Ltd. Anhui Honglu Steel Structure (Group) Co., Ltd., which operates in the metal manufacturing industry, engages in a three-dimensional garage, automatic welding equipment manufacturing, and other intelligent equipment manufacturing fields. Its co-innovation is primarily based on industry and education, with the Hefei University of Technology and Guoyang County Shenghong Science and Technology Co., Ltd. as the only collaborators. Despite being recognized as a high-tech Enterprise in 2022, the technical innovation performance of the metal manufacturing industry could be better. As for the other three state-owned holding companies with policy and resource advantages, they exhibit high technical innovation performance despite low levels of co-innovation. State-owned enterprises should take on social responsibilities and pursue economic benefits(Zhu et al., 2016). Thus, these three enterprises should not avoid knowledge spillover and reduce co-innovation; instead, they should capitalize on their technological leadership, lead other enterprises in the same industry to innovate together and achieve synchronous improvement of technological innovation performance.

In this study, we also examine the ego network of several enterprises and use community discovery algorithms to analyze their co-innovation patterns. Due to the sparseness of the ego network, we employ a greedy search algorithm for community detection and validate the results using other community discovery algorithms, such as the Edge-betweenness algorithm(Sihag et al., 2014). We also display the names of nodes with more than half of the sample number of partners.

The figure presented above illustrates that top-performing PI companies, in terms of innovation, tend to collaborate with universities or institutions. This aligns with Messeni's research(Messeni Petruzzelli et al., 2011), which suggests that collaboration in innovation can lead to increased value. Knowledge-creating alliances formed through school-enterprise cooperation are known to excel in two critical dimensions: boundary spanning and knowledge recombination. These types of alliances enable the utilization of tacit knowledge within cooperative relationships, ultimately creating new knowledge. Furthermore, the benefits of knowledge-creating alliances formed through school-enterprise cooperation extend beyond improved technological innovation performance. These alliances also facilitate the transfer of knowledge and technology from universities and research institutions to enterprises, thus promoting economic growth and social progress(Zhu et al., 2016). Through cooperative partnerships, companies can access academic researchers' expertise and specialized knowledge, who can contribute to developing new technologies and products(Messeni Petruzzelli & Murgia, 2020). Moreover, universities and research institutions can benefit from the funding and resources provided by industry partners, which can support their research and help them to achieve their scientific and technological goals(Caviggioli & Ughetto, 2013; Figueroa & Serrano, 2019).

4.3.2 Representative firms case study

The patent cooperation networks of leading companies in various industries exhibit diverse characteristics, which can be broadly categorized into two types. By studying the R&D cooperation network model of representative enterprises, it is possible to identify strategies for promoting technological innovation through boundary spanning and knowledge recombination. The cooperation networks of industries 3, 4, 5, and 6 form multiple settlements with enterprises focused on product-oriented technology research and development. Meanwhile, industries 1, 2, 7, and 8 exhibit individual network structures and node enterprises emphasizing basic technology research and development. These findings demonstrate that enterprises with varying knowledge requirements must prioritize partnership and cooperation network structures tailored to their specific needs while developing strategies for innovation.

Our analysis reveals two distinct communities in the ego network of the China Nuclear Suvalve Science and Technology Industry Co., Ltd.(CNN): the self-centeredness community and the Harbin Institute of Technology Community. Notably, CNNU has connections with both communities, demonstrating its ability to leverage its partnerships for knowledge flow and innovation effectively. This is particularly impressive given the sensitivity of its industry, which typically makes collaboration with other businesses difficult.

On the other hand, Changchun FAW Fuwei Auto Parts Co., Ltd. has a relatively simple community structure and fewer knowledge resources. However, it collaborates closely with many members of another community, particularly with the Harbin Institute of Technology and Shanghai Jiao Tong University, demonstrating its effective use of university-based innovative resources.

China Zhenhua (Group) Technology Company Limited has three communities in its egocentric network. It is in the same community as Shanghai Jiao Tong University and other communities collaborate with the university, demonstrating that the company's egocentric network draws a significant amount of knowledge resources from the university. China Zhenhua (Group) Technology Co., Ltd. is a subsidiary of the Shenhua Group. This energy company engages in collaborative R&D. It indicates that it places a high value on heterogeneous knowledge and can identify external technological opportunities. Shaanxi Baoguang Vacuum Electric Co., Ltd.'s egocentric network comprises three communities. However, unlike China Zhenhua (Group) Technology Co., it does not include universities, research institutes, or its partners, State Grid and Guangzhou Power Supply Bureau Co.

These findings suggest that effective co-innovation is critical to innovative performance in many industries. While state-owned holding companies have resource advantages, our results suggest that companies with relatively low co-innovation should actively seek to build relationships with other enterprises and universities to achieve synchronous improvement of technological innovation performance. Ultimately, the success of these partnerships will depend on the ability of companies to effectively leverage their resources and work collaboratively with others in their respective industries.

5. Theoretical and practical implications

5.1 Theoretically, PI firms' knowledge strategy dichotomizes into *boundary-spanning* versus *knowledge recombination*

In 1986, the United Nations International Labor Organization first proposed the new concept of “knowledge management”(Wiig, 1997). Later, Peter Drucker formally defined and interpreted the concept of "knowledge management" (KM), distinguished knowledge resources from traditional material resources, and emphasized its essential role in the acquisition of competitive advantage for enterprises(DRUCKER, 1988). Since Zack proposed "knowledge strategy" in 1999, knowledge management and business strategy have gradually merged and developed new concepts(Zack, 1999). Researchers have realized that KM's basic tasks do not achieve KM goals alone, and Rubenstein-Montano et al. point out that the combination of KM and strategic goals has been involved in KM activities(Rubenstein-Montano et al., 2001). As KM is implemented more and more extensively and intensively, the problems and difficulties involved have come to the fore.

"Knowledge strategy" is focused on developing a competitive strategy that builds on an organization's existing knowledge resources and capabilities while also identifying gaps in knowledge that can be turned into strategic gaps(Zack, 2002). The key to effective knowledge strategy management for decision-makers is to dynamically select the most appropriate strategies based on firms' requirements and external environment, thereby organizing systematic competitive strategies based on knowledge resources.

In recent years, researchers have explored the impact of knowledge strategic management on enterprise performance, merging knowledge management and strategic management. Mohsin Shahzad et al. found that knowledge management can improve corporate performance(Shahzad et al., 2020). A study found that the knowledge management process can boost enterprise worker productivity, leading to improved enterprise productivity(Migdadi, 2022). Similarly, an empirical analysis of data from 88 Italian SMEs showed that managing with knowledge can promote extensive data analytics capabilities, improving firm performance(Ferraris et al., 2019).

This paper wants to shed further light on the tacit knowledge of strategical management through joint-patent networks. From the existing studies, the value chain of knowledge assets of

PI enterprises shows that the competitive advantage of technological innovation comes from how enterprises acquire tacit knowledge (mainly cooperative R&D and reverse engineering), as well as the recombining process of acquiring the value of knowledge assets (Martín-de Castro et al., 2013). This research highlights that the comparative advantage of PI enterprises lies in tacit knowledge, which can be managed strategically through boundary spanning and knowledge recombination. PI companies should build strong relationships with knowledge-creating alliances and leverage their network position to promote technological innovation(Figueroa & Serrano, 2019).

5.2 Practically, PI firm source a supply of tacit knowledge through a joint-patent network, and better position advantages

A patent-intensive enterprise joint-patent network can effectively integrate knowledge, realize the complementary benefits of knowledge resources, promote the maximum utilization of knowledge resources within the network, and play an essential role in promoting industrial innovation capability and enhancing industrial core competitiveness(Gertler & Levitte, 2005). Because of the various network location advantages, the enterprises positioned in different network positions have apparent disparities in their ability to gather information and resources. Once players can effectively integrate tacit knowledge from the joint-patent network, the complementary advantages and utilization of knowledge resources are maximum(Filieri et al., 2014).

The contribution of patented technologies to the overall enterprise economy is significantly superior, with successful patent productization and more comprehensive intellectual property protection. The reliance of PI enterprises on technology, intelligence, patents, and other intellectual assets dramatically exceeds that of other industries(Hu & Yin, 2022). Behind the high-tech content of patent-intensive enterprises is the high investment in scientific and technical personnel and R&D capital, which obtains a high yield of intellectual assets in return and, in turn, accumulates capital for continued R&D and innovation(Yu et al., 2022).

In addition, tacit knowledge can assist PI firms in gaining a deeper understanding of their competitors and the industry, enabling them to make informed business decisions(Suppiah & Singh Sandhu, 2011). Meanwhile, tacit knowledge is essential for fostering an enterprise's innovative culture.

Tacit knowledge is hard to be utilized directly and efficiently, making it a valuable resource for companies to gain a competitive advantage (Spender, 1993).

Several researchers argued that individual inventors or economic actors could rarely invent independently and never do so in a vacuum(Messeni Petruzzelli et al., 2011). The idea of knowledge spillovers between economic actors allows enterprises to access new information from their surroundings through processes like technological R&D operation, which requires knowledge interaction(Feldman, 1999; Krugman, 1992; Leone et al., 2022). It is necessarily better to analyze the structure and position of joint-patent networks to understand the tacit knowledge recombination mechanism and determine how to promote technological innovation.

The joint-patent networks consider the flow and sharing of knowledge resources to be the ecological environment and realize technological innovation by forming the cooperation relationship among innovation subjects as the network connection edge(Boschma & Frenken, 2010). How to ensure the participation of the joint-patent networks to achieve the maximum utilization of knowledge resources and enhance innovation performance has drawn the interest of scholars. It is necessary to analyze the structure and characteristics of the joint-patent networks to better understand inter-organizational cooperation and innovation.

Previous studies of scholars on the joint-patent networks often only reveal the network of enterprises in specific technology fields, and the studies mostly start from a simple and single perspective, and the studies on cooperation network of patent-intensive enterprises still lack a comprehensive and systematic understanding, although some scholars have studied collaborative innovation from the perspective of complexity, the studies on cooperation network of patent-intensive enterprises still lack a comprehensive and systematic understanding; Most research findings examine industrial innovation from a static perspective, making it difficult to explain and accurately elaborate the operation and evolution mechanism of joint-patent networks; additionally, research on joint-patent networks of PI enterprises is still underrepresented among scholars.

This paper suggests that in managing their patent portfolios, PI enterprises should prioritize patent cooperation relationships and pay attention to the dynamic balance between exploration and exploitation in the patent cooperation network(Veugelers & Cassiman, 2005). The identification, mining, and utilization of tacit knowledge overflow should be maximized(Gulati, 1995; Uzzi, 1997) through repeated collaborations with existing partners in order to establish higher levels of familiarity, trust, and mutual understanding(Zucker, 1987). Such prior collaboration ties not only make relationships efficient to establish and easy to maintain but also facilitate the transfer of knowledge between actors, thereby favouring economies of time, integrative agreements, Pareto improvements in allocative efficiency, and complex adaptation(Dyer & Chu, 2003; Zollo et al., 2002). Furthermore, trust and reputation play essential roles in mitigating the challenges associated with information asymmetry and causal ambiguity(Lin, 2002; Mora-Valentin et al., 2004), enabling openness to trade partners for value creation through exchange and combination. In the governance structure of R&D collaborations, the trust provides a sociological element of exchange, giving more flexibility in operation and reducing coordination costs by providing the ability to smooth conflicts(Ardito et al., 2019).

6. Conclusion

This paper aims to investigate how PI companies can effectively identify, acquire, and utilize tacit knowledge through the use of cooperative patent networks and knowledge-creating alliances. The study found that a well-balanced two-dimensional structure of control over partners and depth of cooperation leads to higher innovation performance for PI companies. Furthermore, the strategic management of tacit knowledge is divided into boundary-spanning and knowledge recombination, with patent partnerships, particularly school-enterprise partnerships, being beneficial for these processes. These findings were derived from analyzing technical innovation performance, embedded patent cooperation networks, and case studies conducted through the ego network approach.

Knowledge resource management, especially of tacit knowledge resources, is essential for resource structure and innovation cost reduction. In the knowledge-based economy, tacit knowledge strategic management is crucial for PI enterprises, which rely on knowledge resources to enhance innovation and market competitiveness. As the traditional innovation model's limited and unitary knowledge resources cannot support open innovation, technological innovation patterns shift from linear to network as R&D cooperation deepens. Joint-patent networks can help firms identify, acquire, and use tacit knowledge to maximize complementary advantages and knowledge resource use(Mirvis et al., 2016).

This paper focuses on PI enterprises in China and examines their co-innovation position advantage and technological innovation performance using data envelopment analysis (DEA) and social network analysis (SNA). The sample consists of 103 listed firms with more than 500 invention patents and a 5-year R&D history. The BCC output-oriented variable returns to scale DEA model calculates the technological innovation performance of these firms, which is then analyzed by industry using R ggplot2 violin charts. The sample enterprises' joint-patent networks are built using SNA, and an R graph is used to draw the topological structure and calculate the network structure index. The paper aims to generate new technology innovation research ideas by studying patent-intensive enterprises, tacit knowledge resource sharing, and joint-patent networks, which should be addressed in the literature.

In conclusion, this study highlights the importance of strategic knowledge management, especially tacit knowledge resources, for innovation and competitiveness of patent-intensive enterprises. This study provides a valuable tool for these enterprises to optimize their cooperation patterns, thus improving their innovation efficiency. By examining joint-patent network embeddedness and technological innovation performance from the perspective of enterprise and industry, this study aims to generate new research ideas on patent-intensive enterprises, tacit knowledge resource sharing, and joint-patent networks.

There are also some limitations to our research. Due to the choice of patent-intensive listed companies as the research sample for this study, there may be limitations in the availability of certain data in measurement. Much of the study population is lost due to the selection of patent-intensive listed companies with R&D activities over the last five years. Some listed companies may have a missing year in their corporate annual reports and thus will be excluded from the sample for this study. Regarding the methodologies used to measure each dimension of knowledge strategy, this study has only chosen the two dimensions with the most significant impact on innovation activities for further research in exploring the impact of joint-patent network construction on innovation performance. Future research could incorporate the small world of joint-patent networks into the relational analysis, or inventor networks could be built to investigate the impact of internal co-innovation on innovation performance at firms.

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