Full Title:

From Policy to Practice: Structural Evolution of Industry–University–Research Knowledge Networks in the Era of Made in China 2025

Ding-Xuan Huang[a], Chun-Ming Yang[b], Bin-Qiang Tan[c], Yong-jiao Wu[d,*]

[a] School of Management, Chongqing University of Technology, Chongqing 400054, China

[b] School of Economics and Management, Dongguan University of Technology, Dongguan, 523808, China

[c] Institute of Industrial Economics, Jinan University, Guangzhou, 510632, China

[d] Business School, Wenzhou University, Wenzhou, 325000, China

***Corresponding Author**:

Yong-jiao Wu

Business School, Wenzhou University, Wenzhou 325000, China

Email: wuyongjiao@wzu.edu.cn

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E-mail addresses:

huangdingxuan@cqut.edu.cn(D. X. Huang)

2020812@dgut.edu.cn(C.M. Yang)

tanbinqiang@stu2024.jnu.edu.cn(B.Q.Tan)

wuyongjiao@wzu.edu.cn

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Abstract: Collaborative innovation among industry, universities, and research institutes is essential for enhancing a country's innovation capacity. However, few studies have examined how such industry-university-research institute (IUR) collaborative innovation networks evolve before and after the implementation of specific national strategies. To fill this gap, we analyze sensor patent cooperation data from two consecutive periods, before and after the launch of "Made in China 2025 (MiC2025)", to identify distinct types of IUR collaborative networks. We then applied social network analysis to investigate the structural characteristics of China's sensor industry patent cooperation networks (PCNs) and assess the significance of different relational networks. The results show that (1) following MiC2025, the number of patent assignees in sensor industry PCNs increased significantly, accompanied by a lower network density; (2) significant correlations between PCNs across two periods; and (3) state-owned entities hold dominant positions in all types of sensor PCNs. Based on these findings, we recommend sustained support for core technology cooperation and innovation, as along with the development of dedicated innovation platforms.

Keywords： IUR; Relation test; Collaborative networks; Sensor industry

1 Introduction

Industry 4.0 is regarded as a new stage of industrial maturity, based on the connectivity provided by the Industrial Internet of Things (IoT) and the employment of more than a dozen core technologies, including IoT, cloud computing, big data technologies, and blockchain (Benitez et al., 2020; Rad et al., 2022). To facilitate the implementation of the Industry 4.0 plan, the German government proposed the *Industry 4.0* platform plan, which unites business, academic, and political stakeholders. Reischauer (Reischauer, 2018) argued that Industry 4.0 would fundamentally transform the manufacturing industry and contribute to a significant technological revolution in the broader socioeconomic aspect. Other European nations, such as France, Switzerland, and the United Kingdom, have followed Germany's example, establishing national platforms and funding programs with the same or closely similar names to assure the competitive advantage and industrial security of the future economy and society. The initiative has also sparked a discussion regarding the significance of preserving industrial capabilities for national prosperity and innovation (Doblinger et al., 2022; Fox & Mubarak, 2017; Lee et al., 2022; Möldner et al., 2020; Roper & Arvanitis, 2012).

The strategic emphasis on industrial resilience has triggered renewed discourse on the importance of preserving domestic production capabilities as a foundation of national security, particularly in an era marked by geopolitical uncertainty and technological bifurcation (Amaral et al., 2023). Consequently, emerging economies have accelerated efforts to modernize their industrial infrastructures (Băzăvan, 2019). For China, whose industrial base has traditionally relied on labor-intensive models (Li, 2018), such modernization became imperative in response to the global shift toward intelligent manufacturing (Lee et al., 2022). In 2015, the Chinese State Council (CSC) launched the MiC2025 initiative, a policy blueprint aimed at transforming China into a global manufacturing powerhouse through breakthroughs in ten key sectors, including advanced robotics, aerospace, and smart manufacturing systems (CSC, 2015).

Sensor technology occupies a pivotal role in this strategic transformation. As a fundamental component of intelligent systems, sensors underpin real-time information acquisition, thereby enabling the automation and intelligence of manufacturing processes. Notably, seven of the ten priority sectors outlined in the MiC2025 roadmap explicitly involve sensor applications. The policy emphasis continued in *China's 14th Five-Year Plan for Digital Economy Development* (CSC, 2022) , which reaffirmed sensors as critical enablers of technological innovation. However, unlike Germany's institutionally mature Industry 4.0 platform, China's implementation of MiC2025 has faced challenges, namely, a relatively weak initial technological foundation, fragmented stakeholder coordination, and insufficient policy coherence (Wang et al., 2020).

Eight years after MiC2025's introduction, fundamental questions remain: Has the policy stimulated meaningful engagement among IUR in collaborative innovation? Has the structure or density of sensor-related innovation networks evolved in measurable ways? More broadly, to what extent has MiC2025 reshaped the underlying collaborative architecture of China's innovation system? Therefore, this study addresses these questions by empirically analyzing the evolution of sensor-related IUR collaborative innovation networks in China across two distinct time periods: pre- and post-MiC2025 implementation. By leveraging patent co-application data as a proxy for collaboration, we constructed and compared four types of PCNs: Industry-University (IU), University-Research Institute (UR), Industry–Research Institute (IR), and tripartite IUR networks. Applying SNA and the Quadratic Assignment Procedure (QAP), we identify structural shifts and evaluate the statistical continuity of interorganizational collaborations.

The contributions of this research are threefold: (1) It proposes a longitudinal, data-driven framework based on SNA to assess national innovation strategies; (2) It elucidates the policy-induced dynamics of sensor-based innovation ecosystems; (3) It provides targeted insights for enhancing collaborative innovation platforms and improving the governance of core technology development.

This remainder of this article is organized as follows: Section 2 reviews the literature on patent-based collaboration and PCN typologies; Section 3 outlines the methodological framework and data sources; Section 4 presents the structural characteristics of sensor innovation networks; Section 5 reports the results of network relational tests; and Section 6 concludes with theoretical implications, policy recommendations, and future research directions.

2. Literature review

To contextualize the evolution of collaborative innovation networks, this section reviews two key streams of literature: (1) PCNs and their structural, industrial, and spatial characteristics, and (2) IUR collaboration, focusing on its mechanisms, regional dynamics, and innovation impacts.

2.1 Patents and PCNs

Patents are one of the most important legal forms of protection for the results of R&D. It ensures a return on investment in R&D and establishes a core competitive advantage for the organization, and patents are also one of the most commonly used indicators in innovation research (Barberá-Tomás et al., 2011; Liu et al., 2021). Typically, academics use patent-based measures，for instance, monitoring patent citations or co-inventions – to characterize innovation activities, such as mapping knowledge flows and innovation diffusion (Losacker, 2022). Among them, patents and patent citations are the most useful and significant indicators for analyzing technological diffusion and technological evolution; the more frequently a patent is cited by subsequent patents, the greater the degree of diffusion, the broader the scope of application, and the greater the value of the technology (Chang et al., 2009). Gradually, patent citations create a complex network of patents by connecting patent owners and filing dates. Based on the relational characteristics of patent networks, Morescalchi et al. (2015) classified patent networks into several typologies, such as (1) patent citations and (2) co-inventions. Hence, de Paulo et al. (2018) indicate that PCNs are platforms for both industry and regional cooperation and innovation, through which patentees can quickly fulfill specific knowledge innovation needs without having to spend lots of time and money to redevelop them in-house. These conclusions about patent relation networks can assist us in generalizing and summarizing PCNs from three perspectives: the relation characteristics of PCNs, the industrial study of PCNs, and the regional cooperation study of PCNs.

First, from a relational structure perspective, patent collaboration relationships can be loosely connected, informally organized, deeply embedded, or even reintegrated depending on actors' shared innovation goals and knowledge complementarities (Wang et al., 2020). Therefore, Liu et al. (2021) conceptualize PCNs not merely as formal legal collaborations, but as dynamic, evolving social structures that shape access to innovation resources. Structural attributes, such as degree centrality, closeness centrality, betweenness centrality, and network density, are commonly used in SNA to assess how entities function within innovation ecosystems (Tsay & Liu, 2020). These structural elements not only mediate knowledge flows but also influence the innovation outcomes of individual actors (Choi & Hwang, 2014). Furthermore, de Paulo et al. (2018) proposed a multidimensional view of patent influence, including horizontal/vertical and static/dynamic layers, which enables a more profound understanding of technological evolution and the inter-organizational relationships underpinning it.

Second, from the industrial application perspective, a growing body of research has applied PCNs to explore sector-specific innovation dynamics in emerging and strategic industries. The number of patents and patent assignees within these networks has shown an upward trend in various sectors, including the energy storage industry (Guan & Liu, 2016; Wang et al., 2023), the solar photovoltaic industry (de Paulo et al., 2018), the artificial intelligence industry (Tsay & Liu, 2020), and the intelligent manufacturing equipment industry (Li et al., 2021). Key indicators of PCNs, such as degree centrality and closeness centrality, effectively characterize the innovation efficiency of relational networks. For instance, Cen et al. (2022) indicate that network centrality metrics in PCNs positively influence R&D performance; similar findings were reported by Wang et al. (2023). The positive impact of degree centrality on innovation is also evident in urban innovation studies (Liu et al., 2021). Furthermore, Goetze's empirical research demonstrates that the communication role of star inventors within collaborative networks is reflected in both the number and quality of patents (Goetze, 2010). Additionally, the knowledge and cooperation networks within PCNs are often decoupled (Guan & Liu, 2016; Wang et al., 2023). Therefore, Wang et al. (2023) suggest that to leverage development opportunities, it is crucial to consider the partners' stock of knowledge elements in PCNs, particularly in relation to the trends in their future locations. Together, these findings highlight the dual importance of relational embeddedness and knowledge capital in shaping innovation outcomes across industries. They also suggest that PCNs should be analyzed not just as conduits for collaboration, but as strategic architectures that reflect the evolving alignment between knowledge creators, industrial actors, and future technological trajectories.

Third, from a regional collaboration perspective, exploring geographic proximity in PCNs aids in understanding the formation of innovation-led markets within regional contexts and the effects of network activity across regions. This understanding can contribute to innovation diffusion and sustainability (Losacker, 2022). For instance, Yao et al. (2020) utilized a unique longitudinal dataset of patents related to intercity co-invention networks granted in China from 2001 to 2016. Their findings confirm that urban innovation is bolstered when cities are deeply integrated into intercity innovation networks. Additionally, Zhou and Zhang (2021) examined the Beijing-Tianjin-Hebei collaborative innovation network and identified four typical structures: hierarchical, monocentric, polycentric, and flat. They noted a distinct positioning within this network, with Beijing serving as the center of the Beijing-Tianjin-Hebei patent co-invention network, while Tianjin and Hebei were found to be less closely connected. Furthermore, an empirical study involving a sample of 3,101 Spanish firms indicates that those engaged in national or regional cooperation networks and investing in R&D demonstrate a greater propensity to patent compared to firms outside such networks. This study also suggests that the location and type of network influence the benefits firms receive from cooperation (Bolívar-Ramos, 2017). Additionally, research by Morescalchi et al. (2015) reveals that physical distance adversely affects R&D collaboration, as evidenced by consistently higher levels of multinational inventor collaboration in Europe compared to non-European counterparts. In all, these studies underscore the importance of network proximity, structure, and spatial embeddedness in shaping innovation diffusion pathways. They further suggest that effective regional innovation strategies should not only foster local capacity but also strategically integrate peripheral actors and regions to build inclusive, sustainable, and territorially cohesive innovation systems.

Together, these findings suggest that PCNs should be interpreted not merely as relational diagrams but as strategic infrastructures that condition innovation capacity through both structural embeddedness and spatial connectivity.

2.2 IUR collaboration

IURs serve as the central subjects of innovation, reflecting their roles within the social division of labor (Xu et al., 2023). As noted by Zeng et al. . (2023), IUR co-innovation represents a collaborative process wherein firms, universities, and research institutes share and transfer external knowledge to improve technological innovation performance. This collaborative process has two primary characteristics: first, the entities involved in the IUR should share similar knowledge backgrounds and possess strong management skills; second, a higher absorptive capacity among the participating entities facilitates easier and less costly information exchange, thereby promoting innovation. According to de Paulo et al. (2018), as firms increasingly partner with universities and both public and private research centers, the levels of technology cooperation and knowledge exchange among firms experience significant growth. In comparison to firm-level innovation, collaborative innovation and the absorptive capacity of IURs enhance firms' innovation performance, expedite the transformation of results, and optimize industrial structures, particularly when supported by government initiatives. As a result, firms that collaborate with research institutes tend to demonstrate higher levels of innovation (Zeng et al., 2023). Additionally, the research performance of research institutes within IUR collaboration networks is significantly influenced by their position within the collaboration network involving industry or universities; specifically, those research institutes that possess a higher degree of centrality enjoy more opportunities for direct collaboration across various partnerships with industry and universities (Chen et al., 2020).

Rapid technological change has brought industry, universities, and research institutes closer together (Bai et al., 2020). IUR's research currently covers various industries, regions, and even countries. First, the research on the integration of IUR with various industries demonstrates that IUR cooperation in different industries has distinct characteristics. For example, Yin et al. (2020) measured the technical cooperation between carbon capture and storage (CCS) research groups using a global patent cooperation network. Their findings suggest that there are relatively loose partnerships between Chinese CCS companies and related R&D organizations and that these groups' overall cooperation network is still developing. The loose characteristics of the IUR cooperation network for carbon-neutral technologies were also verified in the research work of Zhou et al. (2023). In particular, their results showed that there are several enterprises dominating the cooperation network throughout all stages of the innovation cooperation for clean combustion technologies in China, with little awareness of the participation of research institutes from universities. Correspondingly, Pu et al. (2022) used Patsnap's data to analyze the characteristics of the patent collaboration network in the field of lithium battery energy storage. They found that in the field of lithium batteries, although state-owned energy enterprises or institutions and colleges and universities do not occupy an absolutely dominant position in the collaboration network, they still have a high degree of centrality, and new enterprises and organizations are more inclined to collaborate with organizations with a high degree of centrality when they enter this field.

Regional cooperation research of IUR is reflected not only between cities but also between countries. For example, Song et al.(2020) utilized data envelopment analysis to examine the global impact of IUR collaboration on carbon emissions. They found that (1) the efficiency of China's IUR collaboration is generally on an upward trend, with technological advancement being the primary driving factor; (2) the efficiency of IUR collaboration in many provinces in China has not yet reached the effective frontier, and there is a great deal of room for improvement in the efficiency of IUR cooperation and innovation. Similarly, the suboptimal levels of both IUR R&D efficiency and IUR transformation efficiency are reflected in the study on the impact of pilot innovative city policies on IUR co-innovation in 26 cities in China's Yangtze River Delta, where transformation efficiency is consistently lower than R&D efficiency (Zeng et al., 2023). Moreover, some researchers have analyzed the impact of the location of IUR cooperation based on innovation performance. They argued that the joint establishment of research bases is the most advantageous mode of IUR cooperation to promote enterprise innovation – that is, the IUR cooperation model that is advantageous to enterprise innovation should be oriented towards market value (Cui et al., 2022). In contrast to the above data based on a single country, Hemmert et al. (2014) presented international data. They analyzed survey data from 618 IURs in the United States, Japan, and South Korea to determine how relational mechanisms contribute to the formation of trust in IUR collaborations in the three countries. They discovered that the activities of innovation leaders are a key mechanism for building trust between firms and universities. Therefore, from a public policy standpoint, they suggested that innovation creation networks between firms and universities should be strengthened and that partners should be provided with effective contractual guarantees.

However, existing PCNs research predominantly adopts holistic network perspectives and relies on static patent indicators, overlooking dynamic technological development aspects(Huang et al., 2022; Wang et al., 2020).

2.3 Research gap and research questions

The existing literature provides a robust foundation for understanding PCNs and IUR collaboration across industrial and regional contexts. However, several critical gaps remain. First, most studies examine PCNs and IUR collaboration as distinct analytical domains, with limited efforts to integrate them. Few have investigated how IUR entities (e.g., firms, universities, and research institutes) interact and evolve within PCNs in specific technological domains, such as sensors. This separation constrains our understanding of how actor types shape network structures and innovation outcomes. Second, research onPCNs is predominantly static, focusing on single-point network snapshots rather than longitudinal dynamics. Consequently, the temporal evolution of collaboration networks, especially in response to national strategic initiatives like MiC2025, remains underexplored (Huang et al., 2022; Wang et al., 2020). Since such policies are designed to reshape the innovation landscape, it is critical to investigate whether and how PCNs and IUR structures adapt to these institutional changes. Third, although regional disparities in innovation collaboration have been widely documented, empirical evidence is lacking on how national policies influence the density, centrality, and actor composition of IUR-PCNs over time. Given the sensor industry's foundational role in modern information technology and its prioritization under multiple national plans, it provides an ideal context for investigating dynamic, policy-induced transformations in collaborative innovation networks.

To address these gaps, this study develops a policy-sensitive analytical framework and employs patent cooperation data from the sensor industry to trace the evolution of IUR networks. Specifically, we investigate: (1) How have the structural characteristics of

China's sensor-focused IUR collaborative innovation networks changed before and after the implementation of MiC2025? (2) To what extent do collaboration patterns across the pre- and post-policy periods demonstrate structural continuity versus transformation? By answering these questions, the study seeks to advance theoretical understanding of national innovation governance and cross-sectoral collaboration, while offering policy-relevant insights for the strategic development of emerging technologies in rapidly industrializing economies.

3. Research method and data

This section proceeds in two parts: Section 3.1 presents the key indicators of patent-based SNA and the basic steps of applying the QAP to test sensor PCNs relationships; Section 3.2 details the data sources, retrieval strategy, and cleaning workflow.

3.1. Method

3.1.1. Patent-based indicators in SNA

SNA provides a powerful tool for modeling inter-organizational collaboration in technological innovation systems. In the context of patent data, SNA enables the construction of PCNs, where nodes represent organizations (e.g., firms, universities, or research institutes) and edges represent co-assigned patents, interpreted as collaboration ties (Guan et al., 2021; Liu et al., 2021; Tsay & Liu, 2020; Wang et al., 2020; Wang et al., 2023). This methodology yields a systemic view of networked innovation behavior, revealing not only the structure but also the dynamics of knowledge exchange (Tsay & Liu, 2020). To characterize these networks, three groups of indicators are used as follows.

(1)Node centrality in patent cooperation networks

Node centrality is a core construct in SNA, reflecting the structural prominence and influence of individual nodes (i.e., actors) within a network. In PCNs, centrality metrics are essential for identifying which organizations, such as firms, universities, or research institutes, occupy key positions in knowledge generation, access, and brokerage. These positions shape not only the flow of innovation resources but also the formation of collaboration opportunities and the achievement of innovation performance (Choi & Hwang, 2014; Tsay & Liu, 2020).

To capture these structural characteristics, this study adopts three classical and widely utilized centrality measures: degree centrality, closeness centrality, and betweenness centrality. Each metrics provides a distinct dimension of network positioning. First, degree centrality quantifies the number of direct collaborative ties that a node maintains, reflecting its level of immediate connectivity within the network. A higher degree centrality indicates frequent collaboration with other actors, suggesting active participation in innovation networks and potential access to diverse knowledge sources (Liu et al., 2021). Second, closeness centrality measures how proximal a node is to all others in terms of geodesic (shortest-path) distance. It captures the efficiently with which a node can reach or disseminate information across the network, a factor particularly relevant relevant for rapid knowledge acquisition and diffusion. Nodes with high closeness centrality exhibit strong information accessibility and coordination potential in collaborative R&D contexts (Tsay & Liu, 2020). Third, betweenness centrality evaluates the extent to which a node lies on the shortest paths connecting other node pairs, thereby functioning as a potential information intermediary or gatekeeper. Nodes with high betweenness centrality occupy critical intermediary positions, exerting control over information diffusion and potentially acting as either facilitators or bottlenecks in innovation collaborations (Choi & Hwang, 2014).

The mathematical representations of these centrality measures are presented in Equations (1-a), (1-b), and (1-c), respectively.

$$C_D(i) = \frac{d(i)}{N-1} \tag{1-a}$$

$$C_C(i) = \frac{(N-1)}{\sum_{j=1}^{n} d(i,j)} \tag{1-b}$$

$$C_B(i) = \frac{2}{\left[(N-1)(N-2)\right]} \sum_{j \neq k \neq i} \frac{g_{jk}(i)}{g_{jk}} \tag{1-c}$$

Here, $C_D(i), C_C(i), C_B(i)$ denote the degree centrality, closeness centrality, and betweenness centrality of node i , respectively; N represents the total number of nodes in the network; $d(i)$ is the number of direct links (edges) connected to node i; $d(n_i, n_j)$ represents the number of shortest paths between nodes n_i and n_j; g_{jk} is the number of shortest paths between nodes k and j, $g_{jk}(i)$ represents the counts of shortest paths between between nodes k and j that pass through node i.

Taken together, these three centrality metrics provide a comprehensive assessment of an organization's network influence: degree centrality captures the breadth of collaboration, closeness centrality reflects thespeed of knowledge access, and betweenness centrality indicates control over knowledge flow. By analyzing these measures in both pre- and post-policy networks, this study evaluates how different types of IUR actors occupy structurally influential positions and how these positions evolve in response to national innovation strategies.

(2) Network density and centralization in patent cooperation networks

Network density and centralization are two core structural metrics in SNA, offering insights into the overall cohesion and distribution of power within a network. In the context of PCNs, these indicators help assess the structural maturity and relational architecture of innovation systems, thereby identifying potential bottlenecks and coordination inefficiencies.

Network density quantifies the proportion of actual ties present in the network relative to the total number of possible ties. It reflects the overall level of connectivity and the potential for knowledge diffusion among actors. Mathematically, network density is defined as Equation $(2-a)$,

$$D = \frac{2E}{N(N-1)} \qquad (2-\mathrm{a})$$

where, D denotes the network density; E is the total number of observed edges (collaborative links); N represents the number of nodes (organizations) in the network. A higher network density indicates a more cohesive network with rich interconnections, which can facilitate rapid information exchange and collective knowledge creation. Conversely, a lower density reflects a sparse network, suggesting limited connectivity and potentially fragmented knowledge flows.

Network centralization measures the extent to which a network's structure is dominated by a few highly central actors. It captures structural inequality in node centrality and highlights the presence of dominant hubs or monopolies in knowledge exchange. The network centralization(C) can be calculated according to Equation (2-b).

$$C = \frac{\sum_{i=1}^{N}\left(C_{\max} - C_i\right)}{\sum_{i=1}^{N}\left(C_{\max}^{*} - C_i^{*}\right)} \qquad (2-b)$$

where, C_i denotes the degree centrality of node i, and $C_{\max}$ is the maximum degree centrality observed in the network. Network centralization values range from 0 to 1. A value close to 1 indicates a highly centralized structure in which a single or a small set of nodes controls most interactions, whereas a value near 0 suggests a more egalitarian or decentralized structure. The denominator in Equation (2-b) represents the theoretical maximum of the numerator for a star-shaped network. Taken together, network density and centralization provide a nuanced understanding of PCN structure.

High network density combined with low centralization reflects a distributed and inclusive collaboration pattern.In contrast, low density with high centralization suggests potential bottlenecks and dependence on a few key actors, which may render the network fragility if central nodes fail or withdraw. Moderate levels of both density and centralization may indicate a balanced trade-off between cohesive knowledge diffusion and strategic leadership by central actors. In this study, these indicators are employed to examinethe structural transformation of sensor-related IUR collaboration networks across two time periods, thereby assessing the policy-induced evolution of network architecture and innovation governance.

(3) Influence index (Taylor index) in patent cooperation networks

The Influence index measures the net difference between a node's capacity to influence others and its susceptibility to being influenced, thereby reflecting structural power asymmetries in the network. Unlike degree or closeness centrality, which generally assume symmetric interactions, the influence index explicitly incorporates the directionality of relational power. This makes it particularly well-suited for analyzing hierarchical or unequal knowledge structures, a characteristic often observed in IUR innovation systems.

Let A be the adjacency matrix of a given network, and A^n denote its n-th power, representing the number of indirect links (i.e., influence paths) of length n. The influence index (Taylor influence index) for node i is then calculated as shown in Equation (3).

$$TI_i = R_i^{(n)} - C_i^{(n)} \tag{3}$$

where $R_n(i)$ is the row sum of the i-th row of A^n, indicating the number of nodes that node i can influence at a distance n; $C_n(i)$ is the column sum of the i-th column of A^n, representing the number of nodes that node i can influence at a distance n; and $TI(i)$ denotes the net influence capacity of node i at a specified path length n. A positive $TI(i)$ value indicates that node exerts more influence than it receives, suggesting a knowledge-leading position, whereas a negative value indicates greater dependence on others' inputs, signaling a knowledge-receiving role.

In the context of IUR patent cooperation networks, the Taylor index is used to identify core technological leaders, such as national research institutes and central firms, that exert disproportionate influence over others in the innovation process. It also enables the detection of peripheral or dependent entities, such as new market entrants and smaller universities, which have limited outbound influence. Additionally, the index captures the evolution of collaboration asymmetry over time, particularly before and after significant national policy interventions such as Mic 2025. Unlike general centrality measures that focus solely on positional prominence, the influence index incorporates both directionality and comparative influence, offering insights into how collaboration roles shift and stratify within knowledge networks.

Alongside degree, closeness, and betweenness centrality, density, as well as network density and centralization, the Taylor influence index forms a crucial component of this study's network evaluation framework. Its inclusion enables a more comprehensive assessment of structural transformation in sensor-related IUR collaboration, highlighting not only who is central, but also who leads and who follows in the innovation process.

3.1.2. QAP for relationships test

To rigorously assess the structural relationships and temporal continuity between sensor-related PCNs before and after the MiC2025 policy, this study employs the QAP. QAP is a non-parametric statistical method widely used in social network analysis to evaluate correlations between two relational matrices, effectively addressing the challenges of autocorrelation and non-independence inherent in network data (Huang et al., 2022). By applying QAP, we can determine whether the structural similarities observed across different time periods are statistically significant or merely artifacts of random variation.QAP has been successfully utilized across diverse research domains, such as mapping influential countries in environmental technology networks(Liu et al., 2023), uncovering global green ICT cooperation structures (Li et al., 2022), and exploring governance dynamics in corporate social responsibility (Briseño-García et al., 2022).

In contrast to conventional OLS-based regression methods, QAP does not assume the independence of observations. Instead, it operates by repeatedly the rows and columns of one matrix (usually ≥ 1000 iterations) while holding the structure of the other matrix constant. This process generates a reference distribution of correlation coefficients against which the observed correlation is compared (Lv et al., 2019). Such an approach is especially suitable for inter-organizational collaboration studies, where relational dependencies are intrinsic to the data. The QAP procedure comprises the following five steps.

Step1: Matrix construction. Construct two matrices $X=\left[x_{ij}\right]$ and $Y=\left[y_{ij}\right]$, each representing a specific network ($n \times n$ dimension). X is the adjacency matrix representing inter-organizational collaboration intensity, where x_{ij} indicates the number of collaborations between organizations i and j); Y represents the technology similarity network, where y_{ij} signifies the technology similarity between organizations i and j).

Step2: Observed correlation calculation. Compute the Pearson correlation coefficient r_{XY} between the corresponding cells of the upper (or lower) triangles of matrices X and Y, as shown in Equation (4).

$$r_{XY} = \frac{\sum_i \sum_j \left(x_{ij} - \bar{x}\right)\left(y_{ij} - \bar{y}\right)}{\sqrt{\sum_i \sum_j \left(x_{ij} - \bar{x}\right)^2 \sum_i \sum_j \left(y_{ij} - \bar{y}\right)^2}} \tag{4}$$

where $\bar{x}$, $\bar{y}$ are the mean values of the respective matrixes.

Step3: Matrix permutation. Randomly pertum the rows and columns of one matrix (e.g., Y) synchronously to maintain maxtrix symmetry, and recompute the correlation coefficient r_{perm}^{k} after each permutation $k \in [1, N]$, as shown in Equation (5).

$$r_{perm}^{k} = corr\left(X_{perm}^{k}, Y\right) \tag{5}$$

where r_{perm}^{k} represents permuted correlation coefficient, and X_{perm}^{k} represents the permuted matrix.

Step4: Construct null distribution. Aggregate the permuted correlation coefficients to construct the null distribution, as expressed in Equation (6).

$$Null\ Distribution = \left\{r_{perm}^{1}, r_{perm}^{2}, \cdots, r_{perm}^{k}\right\} \tag{6}$$

Step5: Significance testing(p-value calculation). Evaluate the statistical significance of the observed correlation r_{XY} by determining the proportion of permuted coefficients greater than or equal to it, as expressed in Equation (7).

$$p = \frac{\left|\left\{k : \left|r_{perm}^{k}\right| > \left|r_{XY}\right|\right\}\right| + 1}{K+1} \quad (7)$$

where, $|\cdot|$ denotes the cardinality operator, representing the count of elements in a given set. The statistical significance of the observed correlation coefficient (derived in Step 2) is evaluated by comparing it with the empirical distribution of coefficients obtained through random permutations. A p-value less than 0.05 indicates that the likelihood of obtaining such a correlation by random chance is below 5%, thereby allowing rejection of the null hypothesis.This suggests that the observed correlation is statistically significant, i.e., the structural similarity between matrices is unlikely to arise from random variation. In practical terms, if fewer than 5% of the permuted correlation coefficients are equal to or greater than the observed value, the result falls within the rejection region of the null hypothesis. This provides strong evidence that the relational structure in the observed network is not attributable to stochastic processes, but instead reflects a meaningful pattern.

In line with the research objectives, this study applies the QAP method to test correlations between pre-and post-policy PCNs across four types of IUR networks: IU UR, IR and tripartite IUR networks. Figures 9-12 visualize the QAP results for each PCN type. The significant correlation coefficients obtained ($p<0.05$) indicate structural continuity in IUR sensor collaborations before and after MiC2025. These findings support the hypothesis that national policy has contributed to sustaining and reshaping collaborative architectures rather than fragmenting them.

3.2. Data

To analyze the structure and evolution of sensor-related IUR collaboration networks in China, this study utilizes patent cooperation data as a proxy for innovation relationships. All data were retrieved from Patsnap, a widely recognized commercial patent intelligence platform known for its high-quality structured metadata, applicant harmonization, and detailed cooperation tagging.

3.2.1 Data source and scope

Patent information was obtained from the official website of the China National Intellectual Property Office (CNIPA), which contains complete records of all patent granted since the enactment of China's patent law, including application number, filing date, IPC classification number, applicant (patentee), name of the invention, and other essential fields. These data have been widely used in research on innovation collaboration in China (Liu et al., 2021; Yao et al., 2020; Zhou & Zhang, 2021).

The scope includes: Technology domain, where all patents related to sensors, broadly identified through keywords such as sensor, detection, measuring device, and sensing element in titles, abstracts, or claims; Temporal division, including pre-policy period (1 Jun 2007-31 May 2015) and post-policy period (1 June 2015–31 May 2023); Geographical filter, where all applicants located in Mainland China, including domestic subsidiaries of multinational corporations legally registered in China.

3.2.2 Data retrieval and cleaning strategy

To ensure the reliability and replicability of the social network analysis, a three-stage strategy was implemented to retrieve, filter, and construct patent-based collaboration data for IUR innovation networks in China's sensor technologies. This approach systematically integrates query design, entity normalization, and network modeling across two time periods.

Stage1: Patent retrieval and pre-selection

Patent data were extracted from the Patsnap database using a keyword- and applicant-type-specific retrieval strategy. To capture IUR collaborative activity, three Boolean queries were applied: (1)Invention title ="sensor" AND Applicant=university AND Applicant=company; (2)Invention title="sensor" AND Applicant=university AND Applicant=institute; (3)Invention title ="sensor" AND Applicant=institute AND Applicant=company. These queries ensured the inclusion of sensor patents jointly filed by distinct institutional actors. Only patents with at least two applicants were retained. Results from the three queries were merged, duplicate records were removed, and the dataset constrained to patents filed in Mainland China between 2007-2023, thereby excluding foreign institutions and ensuring national relevance.

Stage 2: Applicant identification and data cleaning

Patent assignee were manually classified into one of three categories: industry, university, or research institute. Institution names were standardized using a hybrid approach that combined fuzzy string matching with manual verification, addressing variant spellings, abbreviations, and translation inconsistencies. To reduce noise and improve network interpretability, applicants with only a single occurrence were excluded.

This process ensured consistency innode identities across all periods and enabled the generation of institutional-type-specific collaboration matrices, which served as the foundation for network construction and inter-temporal comparison.

Stage 3: Network construction and software processing

In the final stage, the cleaned data were transformed into undirected, weighted cooperation networks for IU, UR, IR, and full IUR configurations across both timeframes. Nodes represent organizations, and edges denote co-patenting relationships, with edge weights indicating collaboration frequency between entities. The software ItgInsight was employed to construct and visualize these networks, as well as to extract key social network metrics such as centrality and density. Figures 1 - 8 display the resulting network structures, and Table 1 summarizes changes ina collaboration growth and density changes between the pre- and post-policy periods.

4. Results

The indicators and techniques used in social network analysis are particularly effective for examining the structural characteristics of innovation systems that involve interactions. This methodology facilitates a thorough investigation of technology diffusion across various fields by integrating both quantitative and qualitative technology foresight studies (Linares et al., 2019). This section presents the empirical results based on SNA and QAP applied to sensor-related IUR PCNs in China. The analysis proceeds along three dimensions: (1) the structural traits of collaborative assignees; (2) network-level characteristics before and after the launch of MiC2025; and (3) statistical validation of relational continuity across time periods.

4.1 Structural traits of collaborative patent assignees in sensor innovation networks

The number of patents owned by patentees serves as a significant criterion for their ranking (Sun et al., 2018). Table 3 presents the top 10 collaborative assignees across four types of sensor-related PCNs (IU, IR, UR and IUR) during two policy-defined periods between 2007-2015 (pre-policy) and 2015–2023 (post-policy). A total of 39 unique organizations appear in the rankings, including 17 universities, 9 research institutes, and 13 enterprises. By analyzing the composition and distributional dynamics of these core assignees, five structural traits emerge that collectively reflect the shifting architecture of China's sensor innovation ecosystem under MiC2025's influence.

First, the composition of core collaborative institutions remained relatively stable across both periods, yet their collaborative intensity increased markedly in the post-policy era. Leading state-owned enterprises (SOEs) and elite public universities, such as State Grid Corporation of China, Tsinghua University, and the China Electric Power Research Institute (CEPRI), consistently occupied central positions across all PCN types. However, their engagement deepened significantly after 2015. For instance, State Grid's IUR-related collaborative patents rose from 48 to 237, while Tsinghua University expanded its co-patenting activities from 15 patents (pre-policy) to 186 across three PCNs (post-policy). This surge reflects the mobilizing effect of MiC2025 in enhancing the intensity, scale, and functional diversity of collaborations among established national innovation actors.

Second, the role of private enterprises evolved substantially between the two periods. While private-sector participation was marginal before 2015, the post-policy phase witnessed a consolidation of domestic firms as central innovation contributors, particularly in emerging technology sectors. A notable example is Zhejiang Geely Holding Group Co., whose presence along with its research subsidiaries grew from 40 collaborative patents in the IR and IUR networks (2007-2015) to over 220 patents during 2015-2023 (Figures 3-4, and 7-8). This shift illustrates a structural transition in China's innovation system, wherein private firms in smart mobility, intelligent manufacturing, and sensor integration domains moved from peripheral roles to strategically embedded actors within national technology ecosystems.

Third, several key institutions exhibited clear structural multiplexity by appearing across multiple PCNs within the same policy period, reflecting a high level of relational flexibility and absorptive capacity (Table 3). For instance, State Grid Corporation of China ranked among the top 10 assignees in all four PCNs during 2015-2023, contributing 50 collaborative patents in IU, 215 in IR, 56 in UR, and 237 in IUR networks, making it the most pervasively embedded actor in the post-policy network configuration. Similarly, Tsinghua University was active in three networks during the same period, with 54 patents in IU, 58 in UR, and 74 in IUR. Shanghai Jiaotong University contributed 38 patents in IU, 36 in UR, and 42 in IUR, while Xi'an Jiaotong University appeared with 34 in IU, 56 in UR, and 46 in IUR. This cross-network embeddedness not only illustrates these institutions' ability to traverse institutional boundaries, engaging concurrently with industries, research institutes, and academia, but also signifies their strategic centrality within China's sensor innovation ecosystem. Functioning as multi-domain knowledge brokers, these organizations serve as structural bridges that integrate diverse segments of the national innovation system. Their consistent presence across PCNs enhances both network coherence and adaptive capacity, reinforcing their roles as core nodes in an increasingly complex and policy-driven innovation architecture under Made in China 2025.

Fourth, the post-policy period (2015-2023) witnessed the rising prominence of mission-oriented, application-driven research institutes, reflecting a clear alignment with the strategic priorities outlined in Made in China 2025. In particular, the Beijing Institute of Telemetry Technology emerged as a key actor in both the UR and IUR networks, ranking among the top 10 assignees with 50 collaborative patents in each network. Similarly, the China National Long March Rocket Technology Corporation (CGMRC) appeared in the top 10 assignees of the IR and IUR networks, contributing 50 patents in IR and 50 in IUR. This sharp increase in patent output and network centrality among specialized research organizations indicates an intensification of functional differentiation within the innovation system, where sector-focused institutes play critical technological roles in delivering applied breakthroughs, particularly in strategic sectors such as aerospace, military-grade sensing, and intelligent equipment. Their inclusion among the top collaborators in multiple PCNs highlights a transition from generalized institutional engagement to goal-specific R&D deployment, demonstrating how national policy has incentivized sectoral specialization and applied research orientation in collaborative innovation.

Fifth, the presence of foreign entities in China's sensor-related collaborative innovation networks declined dramatically between the two periods, signaling a major structural shift in the international openness of the innovation system. During the pre-policy period (2007-2015), two international firms (Michelin Technology Inc. and Michelin Research and Technology Ltd.) were each listed among the top 10 assignees in the IR and IUR networks, contributing 5 patents per network, respectively. However, no foreign firms appeared in the top 10 rankings of any PCN during the post-policy period (2015-2023). This complete absence suggests a growing localization of innovation collaboration, driven potentially by multiple factors, involving increasing restrictions on international co-patenting, stronger enforcement of domestic IP frameworks, and a strategic national shift toward technological self-reliance and innovation sovereignty. In the context of MiC2025, which prioritizes endogenous technological capacity in high-stakes sectors like sensors, this withdrawal of foreign actors reflects a broader transformation toward a closed-loop, domestically led innovation model. The resulting collaboration structure appears increasingly insular, where knowledge generation and diffusion are concentrated within domestic institutional boundaries, restructuring the national innovation system's relationship with global technological flows.

In summary, the comparative analysis of top collaborative assignees reveals a hybrid transformation, affirming that MiC2025 has not only stimulated broader participation but also reshaped the structural foundation and strategic orientation of sensor technology innovation in China: (1) from a historically centralized, SOE-led collaboration model toward a more pluralistic, domestically diversified, and functionally differentiated innovation system; (2)While institutional continuity among national champions remains evident, the post-policy landscape is characterized by increased participation from private firms, strategic research institutes, and regionally embedded actors; (3)The disappearance of foreign assignees from the top tiers further underscores the policy-driven reconfiguration toward national innovation sovereignty.

4.2 Network characteristics of IUR-PCNs

According to Liu et al. (Liu et al., 2021), SNA is an effective tool for the analysis of collaborative patent networks. Tables 1 and 2, together with visual insights from Figures 1-8, reveal that China's sensor-related PCNs, comprising IU,IR,UR and IUR structures, experienced dramatic expansion and structural transformation between the pre-policy (2007-2015) and post-policy (2015-2023) periods, in response to the national innovation push under MiC2025.

As Table 1 shows, collaborative scale increased substantially across all networks. The number of collaborative patents rose from 299 to 2574 in the IUR network, from 198 to 1611 in IR, and from 26 to 521 in UR. The corresponding number of entities surged as well (e.g., IUR nodes from 333 to 2,107; IR from 205 to 1,243), indicating broad-based mobilization of institutional actors. Total participants (reflecting repeated engagements) grew markedly, particularly in the IR and IUR networks, suggesting intensification of cross-institutional co-patenting activity. However, despite this quantitative growth, the increase in collaboration edges did not keep pace with the growth in nodes. For instance, in IUR, edges rose from 606 to 5176, while nodes grew even faster, driving a decline in network density from 0.0055 to 0.0012. Similarly, the UR network's density dropped from 0.0481 to 0.0049, even as nodes increased from 47 to 511. These trends indicate that while many new institutions entered the network, a significant proportion remained weakly connected or unintegrated, undermining overall connectivity.

Table 2 further highlights key topological changes in the structural configuration of the networks. Though the average degree increased modestly in most networks (e.g., IUR from 1.82 to 2.457), this was insufficient to counteract the density decline, confirming a shift toward sparser and more fragmented network structures. The number of connected components rose sharply (e.g., in IUR, from 98 to 418), while the component ratio decreased slightly, pointing to increasing fragmentation. Moreover, both average path length (IUR: grew from 3.211 to 5.393) and diameter (IUR: grew from 10 to 17) grew significantly, indicating longer routes for knowledge transmission and reduced diffusion efficiency. These changes suggest that while collaboration expanded horizontally, vertical integration and relational embedding did not keep pace, resulting in a polarized architecture with a highly connected core and a fragmented periphery. Despite this peripheral dispersion, core actors became more densely interconnected, as shown by rising K-core indices (IUR: from 3 to 7) and in-degree H-indices (IUR: from 6 to 19). These metrics signal that elite actors, such as central SOEs and top-tier universities, deepened their mutual linkages, enhancing the cohesion and functional capacity of the network's structural core.

These quantitative patterns are vividly illustrated in Figures 1-8. The pre-policy networks (Figures 1, 3, 5, and 7) appear visually compact and clustered with clear core-centered layouts, especially in UR and IR networks. In contrast, the post-policy networks (Figures 2, 4, 6, and 8) are much larger in size but exhibit more fragmented topologies, with numerous peripheral nodes and disconnected subgroups. The visual dispersion of the post-2015 networks aligns with the empirical rise in components and network diameter, and the decline in density, despite the exponential increase in data volume and participant count. These visual and structural trends confirm that MiC2025 has significantly expanded the scale and inclusiveness of sensor-related collaboration, but simultaneously introduced challenges of network integration, coordination, and knowledge flow.

Taken together, these resultss point to a structural duality in the evolution of China's sensor innovation networks that a densifying core comprising key state actors and research powerhouses, coexisting with an increasingly dispersed and fragmented periphery. This configuration reflects both the success of national policy in mobilizing participation and the emerging need for targeted mechanisms to strengthen core–periphery linkages, improve network navigability, and sustain relational cohesion in the face of rapid system expansion.

4.3 Relation-relation test of PCNs

To comprehensively assess the temporal evolution of China's sensor-related PCNs under the influence of the MiC2025 policy, this study employed the QAP to evaluate structural persistence across four distinct network types (IU,IR,UR and IUR, covering two policy-defined periods of the pre-policy phase (2007-2015) and post-policy phase (2015-2023).

The QAP results (Figures 9-12) provide robust statistical evidence of relational continuity across all network types. Specifically, the Pearson correlation coefficients between corresponding adjacency matrices are significantly positive (IU: r=0.331, p=0.002; IR: r=0.384, p=0.003; UR: r=0.417, p=0.001; IUR: r=0.366, p=0.001), all exceeding the 95% confidence threshold. These results suggest that while the composition and scale of the networks evolved under MiC2025, the core relational configurations (i.e., who collaborates with whom) have remained stable over time. This persistence reflects a strong degree of organizational path dependency and supports the hypothesis of cumulative innovation trajectories in complex technological domains such as sensors. It also underscores the stabilizing effect of central institutions—such as State Grid Corporation of China, Tsinghua University, and CEPRI—which have historically anchored the structure of China's innovation system and continue to do so across both periods.

In contrast to the stable relational architecture revealed by QAP, the density-based structural indicators (Figures 13-14 and Table 2) identify significant topological transformations. The density of the IR network declined from 0.0091 to 0.0021, and the

UR network from 0.0481 to 0.0049 across the two periods, with both changes confirmed as highly significant (bootstrap t = 8.57 and 9.30, standard t = 25.42; all p < 0.001). While the number of participating nodes surged (e.g., IR from 205 to 1,243 and UR from 47 to 511), the relative sparsity of links increased, indicating that network expansion outpaced the formation of new ties, leading to lower cohesion and higher fragmentation. This is further evidenced by the rise in network components (IUR: from 98 to 418), average geodesic distance (IUR: 3.21 to 5.39), and diameter (IUR:10 to 17), collectively suggesting that the sensor innovation ecosystem has transitioned from compact, centralized collaboration structures to more fragmented, core–periphery architectures.

This dual pattern of structural dispersion amidst relational stability reflects a critical trade-off inherent in large-scale policy-induced innovation mobilization. On one hand, MiC2025 succeeded in broadening participation by incentivizing a diverse range of organizations to engage in co-invention activities, thereby democratizing access to national innovation resources. On the other hand, many of the newly integrated actors, (often smaller enterprises or regional institutions) remained peripherally embedded, forming few or isolated links with core players. Consequently, the collaborative depth and network redundancy necessary for resilient knowledge diffusion and long-term innovation capacity may be lacking in the peripheral segments.

4.4 Sythnesis analysis

A synthesis of the preceding analyses reveals that China's sensor-related PCNs have undergone a dual transformation of scale expansion and structural reconfiguration in the context of MiC202. This evolution exhibits that MiC2025 catalyzed a broader and more inclusive sensor innovation ecosystem but also introduced new structural challenges.

The resulting networks are simultaneously more complex, more polarized, and more reliant on cohesive core actors to maintain functional integration: ⑴ The collaborative network scale expanded dramatically across all four PCN types, with increased numbers of actors and ties, reflecting broader institutional participation and stronger national innovation mobilization; ⑵ However, this expansion was accompanied by growing structural fragmentation, as many new participants remained peripherally embedded, leading to decreased density, increased components, and reduced network cohesion; ⑶ Despite peripheral dispersion, the network core, composed of central state-owned enterprises, elite universities, and key research institutes, became more densely interconnected and functionally cohesive, strengthening its integrative capacity; ⑷ The institutional landscape diversified, with private firms and mission-oriented research organizations playing increasingly central roles, while foreign actors receded from the top ranks, indicating a realignment toward domestic innovation sovereignty and sectoral specialization; ⑸ Underlying these structural changes, the core relational patterns exhibited temporal continuity, as evidenced by the persistence of collaboration linkages across periods, suggesting strong path dependence and organizational memory in the sensor innovation system.

5. Discussion

5.1 Discussion

Building on the empirical findings, this section interprets the observed structural dynamics of China's sensor-related patent cooperation networks within the broader frameworks of innovation systems theory, network science, and industrial policy. Rather than restating quantitative results, the discussion focuses on unpacking the mechanisms, theoretical implications, and policy relevance underlying the network transformations triggered by Made in China 2025. The following subsections elaborate five key aspects: (1) the expansion of actor participation; (2) emerging structural fragmentation; (3) reinforcement of core–periphery patterns; (4) shifts in international engagement; and (5) theoretical contributions to innovation network research.

(1) Policy-induced expansion of innovation actor base

This study confirms that MiC2025 played a catalytic role in expanding the collaborative scope of China's sensor innovation system. Compared with previous studies that emphasized elite-centric innovation structures dominated by SOEs and top universities (Guan & Chen, 2012; Liu & White, 2001; Wang et al., 2020) , our findings suggest a broadened actor base, as evidenced by the surge in collaborative nodes (e.g., IUR networks expanded from 333 to 2107 participating entities), and the appearance of 13 private firms and 9 mission-oriented research institutes in top-10 assignee lists (Table 3). This expansion reflects the mobilizing capacity of mission-oriented innovation policy

(McLaren & Kattel, 2025), especially when deployed through sector-specific instruments.

Notably, firms like Geely Group and institutes like Beijing Institute of Telemetry Technology emerged as central actors in the post-policy period, which prior literature had not observed in earlier industrial policy phases. Earlier studies emphasized that China's innovation collaboration was largely concentrated among top-tier public universities and SOEs, typically orchestrated through administrative hierarchies or national megaprojects (Guan & Chen, 2012; Liu & White, 2001; Wang et al., 2020). In contrast, our findings illustrate that sector-specific policy targeting, particularly in smart vehicles and aerospace applications, has facilitated the rise of non-traditional actors with application-oriented capacities. These findings depart from established narratives of top-down administrative coordination, suggesting that horizontally structured, policy-enabled mechanisms may be instrumental in promoting a more diverse and functionally differentiated innovation ecosystem, that an institutional evolution yet to be fully examined in the industrial policy literature (Mao et al., 2020).

(2) Fragmentation and the limits of scale-based expansion

Despite the scale expansion, our results show that increased participation did not translate into stronger structural cohesion. Network-level metrics reveal a sharp decline in density across all PCNs (e.g., IUR from 0.0055 to 0.0012), a fourfold increase in disconnected components, and a rise in average path length and diameter (IUR path length from 3.21 to 5.39). These findings contrast with assumptions in classical National Innovation Systems (NIS) theory (Guan & Chen, 2012), which posit that actor diversity enhances learning through interaction. Instead, our results align more closely with network-based critiques (Powell et al., 2005), which emphasize a trade-off between connectivity and cohesion, as the scaling of the system often brings in numerous new participants who remain weakly embedded in the network structure. The presence of structurally peripheral actors, particularly newer private firms and local institutions, suggests that coordination and relational integration have lagged behind policy-driven mobilization, thereby introducing risks of network fragmentation and inefficient knowledge diffusion. This underscores that participation without meaningful embeddedness may ultimately undermine the systemic benefits typically associated with expanded scale.

(3) Reinforcement of core-periphery polarization

While MiC2025 catalyzed broader participation, our findings reveal that it also reinforced the structural centrality of incumbent elite actors, particularly large SOEs and leading universities. For example, State Grid Corporation of China appeared in the top 10 assignee lists across all four PCNs during the post-policy period, and Tsinghua University participated in three out of four networks, with significantly increased collaborative outputs (Table 3). These patterns suggest a path-dependent consolidation of power within a relatively closed core, aligning with institutional lock-in theory (Chen et al., 2023). Prior research has documented the dominance of core actors in China's innovation system (Liu & White, 2001), but our longitudinal network evidence shows that these actors not only persisted but intensified their central positions through multi-domain, cross-network engagement.

Notably, the increase in the IUR network's K-core value from 3 to 7 between the two periods indicates a significant deepening of core structural density. This suggests that while the overall network became more dispersed and fragmented, a subset of central actors became more tightly interconnected, reinforcing a hierarchical innovation architecture. Such high K-core clusters are typically associated with relational durability, mutual reinforcement, and preferential access to knowledge flows, making them critical hubs for sustained collaborative innovation. However, this also implies a growing relational asymmetry: although more actors were mobilized, many remained structurally disconnected, while core actors increasingly function as gatekeepers of collaborative resources and innovation direction. Contrary to assumptions that broader actor inclusion would diffuse power more evenly (Guan & Chen, 2012), our findings suggest that top-down industrial policy may unintentionally entrench existing hierarchies, rather than democratize access to innovation networks.

(4) Strategic localization and the decline of international collaboration

One of the most striking shifts identified in this study is the complete disappearance of foreign firms from the top 10 collaborative assignee rankings during the post-policy period (2015-2023), in contrast to the pre-policy phase (2007-2015), where foreign entities such as Michelin Technologies and Michelin R&D Ltd. each held positions in the IR and IUR networks, contributing five collaborative patents each (Table 3). This change suggests a clear break from the previous trend of limited but visible international co-patenting activity. This divergence stands in contrast to prior empirical studies that highlighted China's growing integration into global knowledge networks through crossborder co-invention and joint R&D ventures (Zhang et al., 2023). The post-2015 retreat likely reflects the compounded effects of MiC2025 's strategic objectives, including increased national emphasis on IP localization, indigenous innovation, and technological self-reliance, particularly in strategic industries such as aerospace, AI, and smart manufacturing. Moreover, the growing policy emphasis on secure and controllable innovation ecosystems may have created institutional disincentives for foreign entities to participate, including administrative barriers, data security requirements, and exclusion from major funding channels.

While such localization may serve national strategic goals, it also raises concerns about the erosion of international learning channels, which are vital for maintaining absorptive capacity (Cohen & Levinthal, 1990) and avoiding technological path dependency. Without sustained international engagement, particularly in high-end, rapidly evolving technological domains, China's sensor innovation ecosystem may face mounting risks of cognitive lock-in (Bellink & Verburg, 2023), diminished exposure to frontier knowledge flows (Archibugi & Pietrobelli, 2003), and ultimately declining marginal returns to domestic collaboration efforts (Dodd et al., 2018). The inward shift observed in this study thus reflects a strategic policy trade-off between reinforcing national innovation sovereignty and sustaining global integration (Dagar et al., 2024). These findings underscore the importance of adopting selective openness strategies (Balka et al., 2014) that maintain critical channels for global exchange while securing national interests in strategically sensitive sectors.

(5) Theoretical contributions and implications for innovation systems research

Beyond its empirical insights, this study makes several theoretical and methodological contributions to the understanding of how state-led industrial policy shapes collaborative innovation network structures in latecomer economies. First, our findings demonstrate that MiC2025 induced a dual transformation of the sensor innovation system like an expansion in participant diversity and a deepening of relational polarization. This challenges the linear assumptions in classical NIS theory (Guan & Chen, 2012), which often equate actor inclusion with improved systemic performance. Although participation across all PCNs increased significantly, the simultaneous decline in network density (e.g., IR from 0.0091 to 0.0021; UR from 0.0481 to 0.0049) and the rise in disconnected components (e.g., IUR from 98 to 418) highlight that inclusion alone does not ensure integration or learning efficiency.

Second, our analysis of structural cohesion reveals that relational inequality intensified over time. The rise in the IUR network's K-core value from 3 to 7 indicates the consolidation of a tightly connected core, comprised mainly of elite universities and central SOEs. This aligns with institutional lock-in theory (Chen et al., 2023), suggesting that rather than disrupting dominant structures, industrial policy can reinforce core–periphery architectures through incentive concentration. Moreover, the persistence of structural multiplexity among key actors, appearing across multiple PCNs, reveals the strategic relational flexibility that policy tends to reward. This directly challenges views that network structures evolve organically from bottom-up collaboration, and instead underscores the designable nature of coordination mechanisms in shaping innovation hierarchies.

Methodologically, this study also contributes by combining longitudinal SNA with institutional typologies and organizational roles to uncover how relational structures evolve across time in response to targeted policy interventions. By integrating network indicators such as average degree, component ratio, and path length with organizational classifications (SOEs, universities, research institutes, and private firms), we capture a multi-dimensional picture of structural evolution. This moves beyond the treatment of policy as an exogenous input, instead conceptualizing policy as an endogenous force that shapes relational configurations over time through selective inclusion, exclusion, and reward systems.

Furthermore, the application of the QAP provides an additional layer of theoretical and empirical insight. While prior studies have used SNA to map IUR innovation networks across industries (Xu et al., 2023; Zhang & Wang, 2022), this study uniquely employs QAP to statistically validate the persistence of collaboration structures in China's sensor sector before and after MiC 2025. The statistically significant correlation coefficients across all four PCNs suggest that relational continuity persists, despite rapid expansion and structural change. This persistence implies that historical collaboration ties, once established, become sticky assets, contributing to entry barriers for new actors while enhancing knowledge retention and stability for incumbents.

This relational stability reinforces the idea that technological innovation is path-dependent and relies on enduring collaboration between inventors and institutions (Nam

& Barnett, 2011). IUR ties, in particular, are shaped not only by formal institutional mechanisms, but also by cognitive proximity and interpersonal trust (Balconi & Laboranti, 2006). By embedding these collaborative ties within long-term networks, organizations can benefit from resource complementarity, knowledge flow continuity, and cross-sector synergies, which are essential for scaling up innovation performance (Zhang & Wang, 2022).

The broader implication is that IUR collaboration functions as a systemic driver of regional innovation capacity, enabling optimal reallocation of technological resources and promoting cross-sectoral industrial upgrading (Cui et al., 2022). For patent applicants, tracking not only the current position of potential collaborators, but also their historical and strategic relational trajectories, becomes increasingly important for identifying high-value partnerships and emerging innovation trends (Wang et al., 2023).

Finally, this study extends the literature on patent-based innovation system analysis (Linares et al., 2019; Liu et al., 2021; Tsay & Liu, 2020). Leveraging SNA and patent data in tandem, we demonstrate that patent cooperation networks can serve as effective proxies for identifying shifts in organizational roles, innovation clustering, and structural integration. As shown in prior studies (Cen et al., 2022), increased size and centrality of cooperation networks tend to enhance R&D performance, whereas excessive density can generate coordination costs. Our findings further confirm that while the number of patent assignees in China's sensor innovation ecosystem grew dramatically, cooperation density declined, revealing a structural tension between openness and cohesion.

Taken together, this study provides a multi-level analytical framework for examining how innovation systems evolve under targeted industrial policy. It highlights the need to move beyond static assessments of actor composition or R&D input, toward approaches that foreground relational cohesion, coordination infrastructure, and network resilience. In latecomer economies facing complex global pressures, these dimensions are critical for achieving long-term innovation capability and policy effectiveness.

5.2. Managerial implications

Building on the empirical results and structural insights outlined above, this study offers two key policy implications for advancing China's sensor innovation ecosystem under mission-oriented industrial strategies such as MiC2025. These recommendations are informed by both the observed dynamics of the PCNs and broader innovation system theory.

First, the findings highlight the need for sustained and strategically coordinated support for cooperative innovation in foundational and enabling technologies. As demonstrated in Figures 9-12, all four PCNs (IU, IR, UR, and IUR) exhibited statistically significant structural persistence across two policy phases (2007-2015 and 2015-2023), with QAP correlation coefficients ranging from 0.331 to 0.417. This continuity indicates that technological collaboration trajectories are path-dependent, evolving cumulatively rather than disruptively (Kim et al., 2016). However, the same period also witnessed increased structural fragmentation and peripheral isolation, especially in the expanded IUR networks (Table 2), suggesting that scale alone does not secure cohesion. To address this, governments must establish dedicated coordination mechanisms that strengthen relational integration alongside scale expansion. In the context of China's emerging sensor sector, characterized by rapid technological convergence and high knowledge intensity (Hu, 2022), existing administrative structures remain poorly adapted to orchestrate cross-institutional collaboration. Specialized IUR liaison platforms should therefore be instituted to align innovation pathways with industry needs and to oversee phased funding schemes tied to Technology Readiness Levels (TRLs). This policy design would complement the observed structural inertia in collaboration networks with targeted institutional flexibility. Moreover, prior studies underscore that IUR collaboration is not only positively correlated with national innovation capacity (Song et al., 2020), but also enhances the rate and quality of knowledge recombination, especially when linked to R&D investment cycles (Pu et al., 2022). Therefore, beyond increasing fiscal input, policymakers should focus on system-building functions: strengthening early-stage basic research pipelines, cultivating interdisciplinary talent pools, and embedding researchers within long-term, policy-supported collaboration structures (Cao et al., 2022).

Second, the spatially uneven diffusion of innovation and the structural peripheralization of new entrants point to a clear need for localized IUR platforms that reflect regional innovation geographies. As shown in Figures 2, 4, 6, and 8, the post-policy networks are larger in scope but structurally more dispersed, with sharply increased numbers of disconnected components (e.g., IUR: rose from 98 to 418) and elongated geodesic paths. These network features, particularly when tied to smart sensor technologies, classified as quintuple-intensive sectors involving talent, capital, R&D,

knowledge, and infrastructure (Hu, 2022), require geographically embedded governance mechanisms. Complex innovation domains such as sensors exhibit high knowledge viscosity and context-specific technical routines, which rely heavily on proximity-based learning and trust-based informal exchange (Losacker, 2022). Empirical research indicates that innovation capacity is positively correlated with the strength of relational networks: cities with strong social capital tend to be more innovative because lower transaction costs and enhanced resource sharing foster idea generation and implementation (Schillebeeckx et al., 2020). This benefit arises from relational embeddedness, which promotes trust-based knowledge spillovers within localized economic systems; geographic proximity, in turn, supports frequent informal interactions and a depth of contextual understanding that formal contracts alone cannot achieve (Yao et al., 2020). Therefore, governments should strategically invest in territorially anchored collaboration infrastructure to reinforce relational embeddedness, particularly in rising innovation clusters beyond core metros. Thus, a three-pronged policy framework is recommended to operationalize this localized approach: (1) Establish sector-specific IUR hubs in key innovation corridors (e.g., Yangtze River Delta, Greater Bay Area) to leverage geographic knowledge externalities, promote co-location of innovation actors, and reduce relational transaction costs; (2) Institutionalize cross-sector collaboration protocols, including standardized IP governance, co-invention recognition mechanisms, and neutral dispute resolution systems, to foster institutional trust and repeated engagement across public–private divides; and (3) Launch talent circulation programs (e.g., dual appointments, regionally portable benefits, innovation fellowships) that facilitate mobility between universities, research institutes, and firms, thereby reinforcing cognitive proximity and enabling systemic learning.

Taken together, these recommendations underscore that successful industrial upgrading requires more than capital injection or actor mobilization. It demands coordinated governance of innovation relations, combining structural continuity with relational integration, and national strategy with regional adaptation. Aligning innovation policy with evolving network architectures is essential for transforming relational scale into systemic resilience.

5.3 Research limitations and future directions

While this study provides valuable insights into the structural transformation of China's IUR innovation collaboration networks in the sensor sector under the MiC2025 initiative, several limitations warrant discussion. First, the analysis relies exclusively on patent co-assignee data, which, while commonly used as a proxy for innovation collaboration, may not comprehensively capture informal, unpublished, or non-patent-based interactions. Future research could benefit from the inclusion of publication data, project grants, or firm-level interviews to better triangulate the relational dynamics of innovation. Second, although the focus on the sensor industry is justified by its strategic relevance within MiC2025, this emphasis limits the generalizability of the findings. Sector-specific institutional logics, value chains, and knowledge intensities might result in different collaboration trajectories in other strategic sectors, such as artificial intelligence (AI), biopharmaceuticals, or advanced materials. Comparative studies across various sectors could help determine whether the observed patterns reflect broader mechanisms of state-led innovation or dynamics specific to the sensor sector. Third, while the network-level analysis provides macro structural insights, it does not fully explore the micro-level motivations, capabilities, or absorptive capacities of individual actors. Combining SNA with case studies or qualitative network ethnography may reveal the organizational routines and behavioral foundations that underlie the observed structures. Finally, although this study employs longitudinal data and QAP to assess network continuity, future research could incorporate dynamic modeling approaches, such as stochastic actor-oriented models (SAOM) or agent-based simulations, to more effectively capture the endogenous evolution of innovation networks over time and in response to policy shocks. Addressing these limitations will foster a deeper understanding of the interplay between innovation policy, institutional coordination, and relational transformation, particularly in latecomer economies navigating the dual pressures of global competition and national techno-sovereignty.

6. Conclusions

This study investigated the structural evolution of China's sensor PCNs across four key sensor-related PCNs (IU, IR, UR, and IUR) during the pre- and post-MiC2025 policy periods. By combining SNA and QAP techniques, we revealed how state-led innovation policy interacts with relational architectures to reshape collaborative innovation dynamics in an emerging strategic industry.

Our results show that MiC2025 effectively expanded the actor base of the sensor innovation system, integrating private enterprises and mission-oriented research institutes alongside incumbent SOEs and elite universities. However, this scale-driven inclusion was not matched by improvements in structural cohesion. Instead, the networks became increasingly fragmented, with many new actors occupying the periphery. Moreover, the persistence of core–periphery asymmetry, measured by increased K-core values and path length, suggests that policy incentives reinforced the dominance of central actors, rather than flattening the innovation hierarchy. Simultaneously, we observed a retreat of foreign actors from the core cooperative landscape post-MiC2015, signaling a transition toward a more localized, techno-sovereign model of innovation governance.

These findings generate three key theoretical insights. First, they challenge linear assumptions in traditional NIS theory by showing that increased diversity does not automatically enhance systemic learning or network resilience. Second, they emphasize the designable nature of collaborative structures—that network configurations are not merely emergent but actively shaped by policy instruments, sectoral priorities, and coordination mechanisms. Third, they underscore the importance of relational cohesion and integration, not just participation scale, as critical dimensions of innovation system performance, particularly in complex, interdisciplinary domains like smart sensors.

From a methodological perspective, this study advances the use of SNA and QAP in patent-based innovation analysis by capturing both structural evolution and relational continuity across policy regimes. The integration of network metrics with organizational typologies enables a more granular and dynamic understanding of innovation systems, especially in transitional economies.

Practically, the study calls for more nuanced policy designs that go beyond actor mobilization to address the coordination and embedding of collaborative relationships. National-level strategies must be complemented by regionally embedded innovation platforms, adaptive governance mechanisms, and support for long-term trust-based interaction across institutional boundaries.

While MiC 2025 has stimulated the growth and diversification of the sensor innovation ecosystem, the resulting network architecture reflects both the strengths and limitations of state-driven innovation in latecomer contexts. Future policy must balance inclusion with integration, autonomy with openness, and short-term mobilization with long-term systemic resilience.

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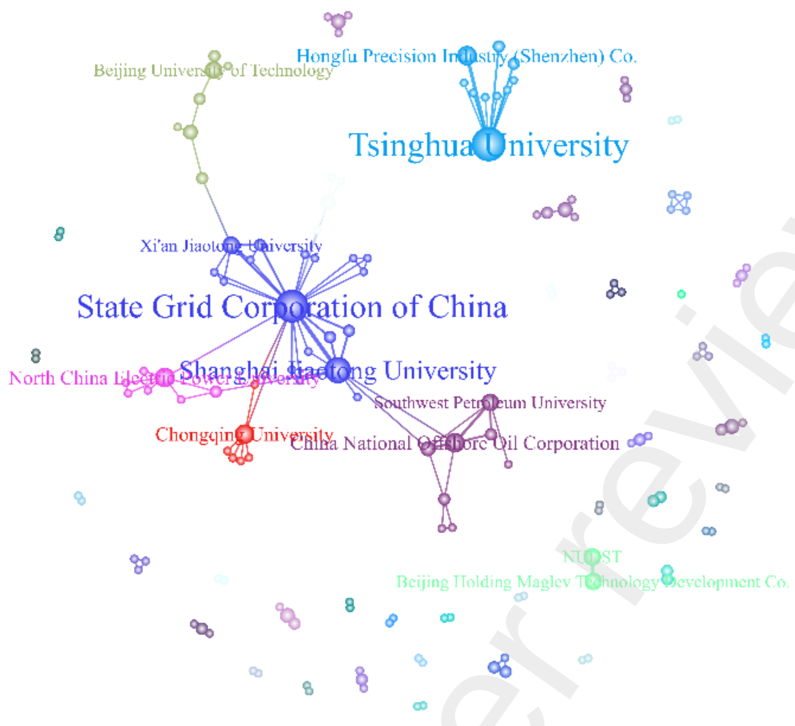


Fig.1. IU network from 2007 to 2015

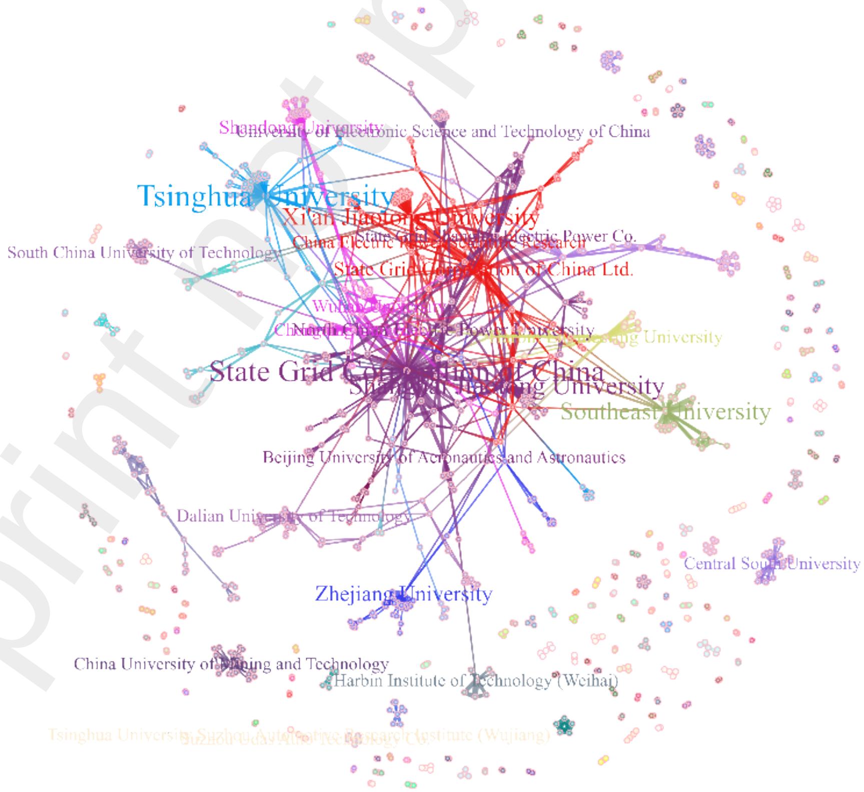


Fig.2. IU network from 2015 to 2023

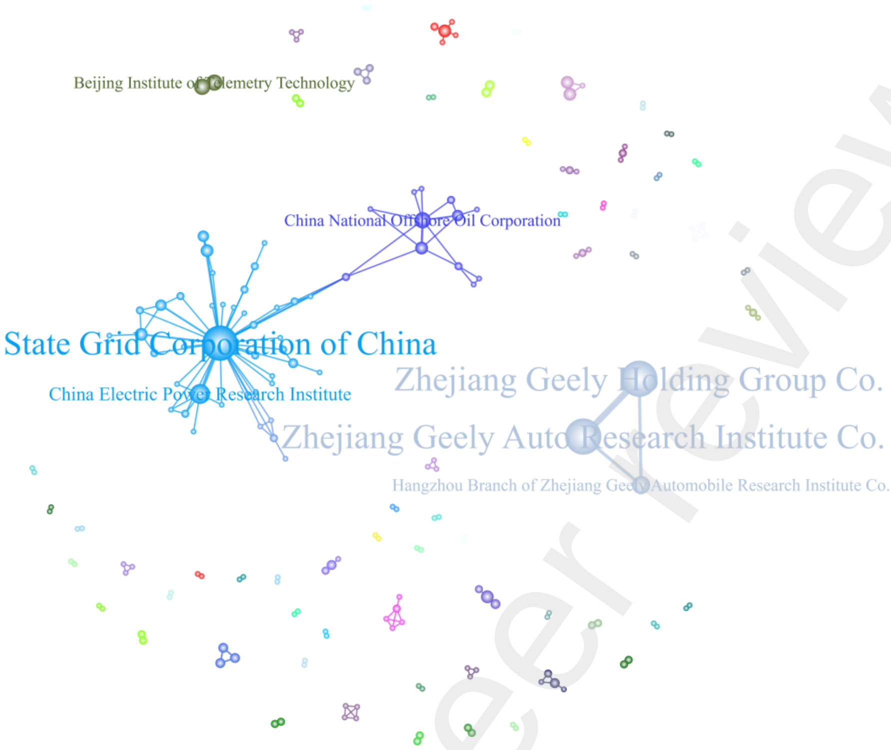
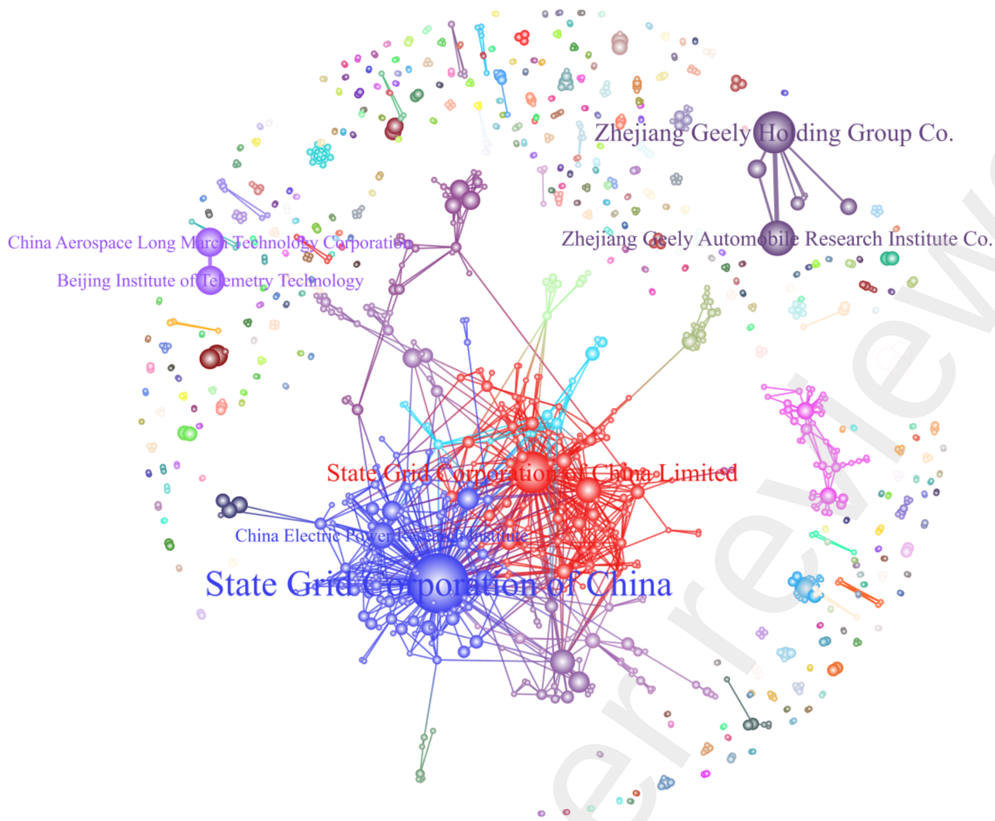


Fig.3. IR network from 2007 to 2015



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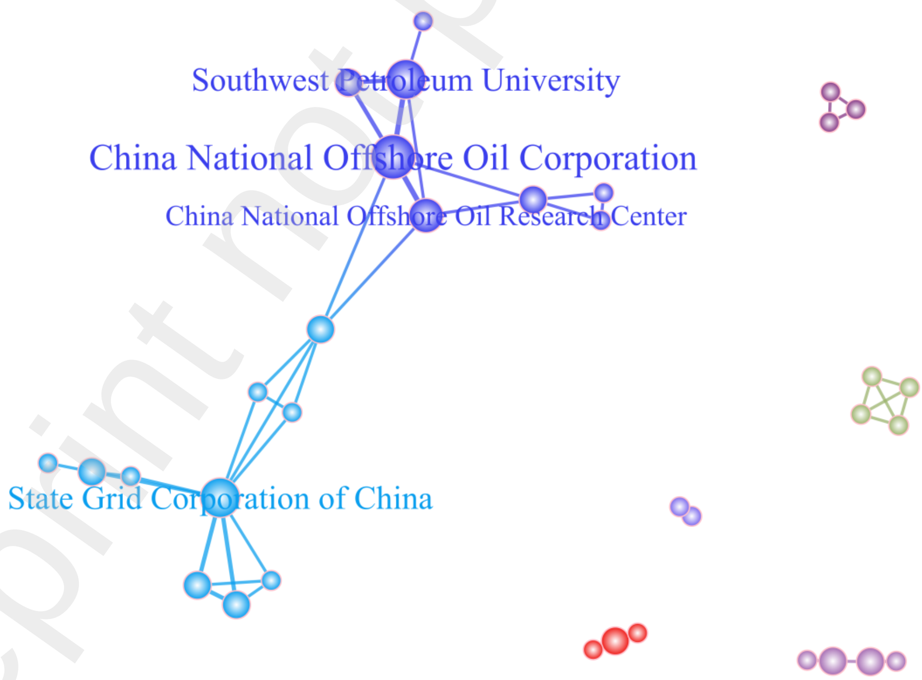

Fig.5. UR network from 2007 to 2015

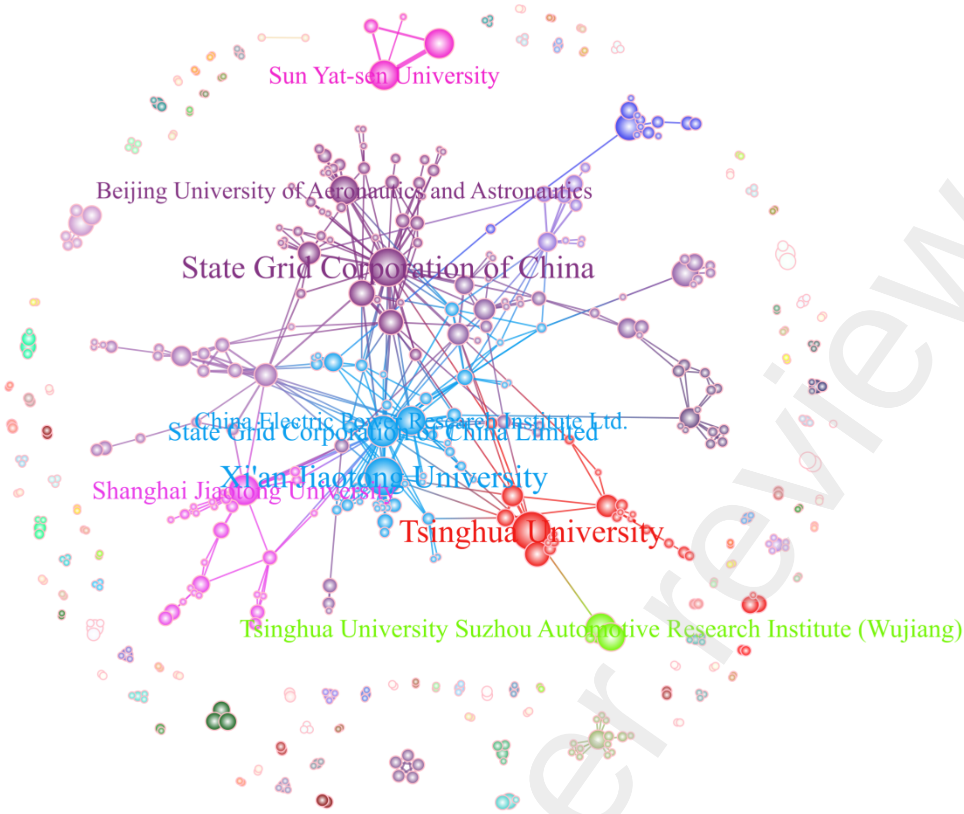

Fig.6. UR network from 2015 to 2023

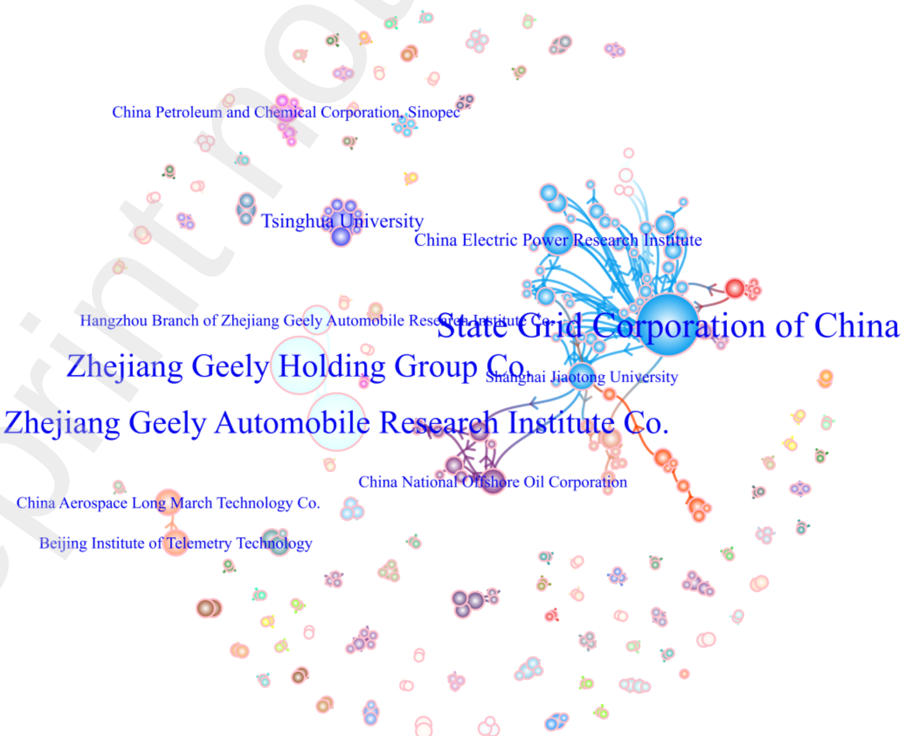

Fig.7. IUR network from 2007 to 2015

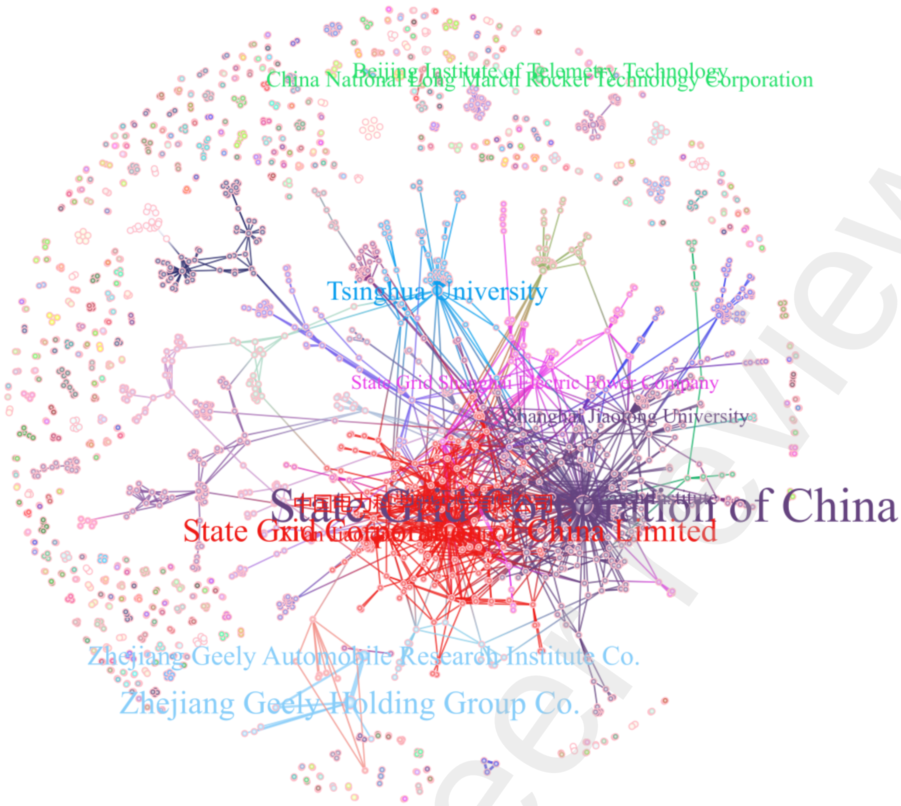

Fig.8. IUR network from 2015 to 2023

		1	2	3	4	5	6	7	8
		Obs Value	Significa	Average	Std Dev	Minimum	Maximum	Prop >= O	Prop <= O
1	Chi-Square	891.312	0.009	32.346	256.776	0.304	7636.668	0.009	0.993
2	Correlation	0.056	0.001	0.000	0.003	-0.000	0.079	0.001	1.000
3	Jaccard	0.009	0.001	0.000	0.000	0.000	0.009	0.001	1.000
4	EntailXY	0.010	0.001	0.000	0.000	0.000	0.010	0.001	1.000
5	EntailYX	0.081	0.001	0.002	0.004	0.000	0.081	0.001	1.000
6	Cramers V	0.016	0.009	0.001	0.003	0.000	0.046	0.009	0.993

Fig.9. Network relations test on IU 2007to2015 and IU 2015to2023

		1	2	3	4	5	6	7	8
		Obs Value	Significa	Average	Std Dev	Minimum	Maximum	Prop >= O	Prop <= O
1	Chi-Square	752.588	0.006	30.561	345.343	0.231	9593.155	0.006	0.995
2	Correlation	0.023	0.004	0.000	0.003	-0.001	0.047	0.004	0.998
3	Jaccard	0.012	0.001	0.000	0.001	0.000	0.012	0.001	1.000
4	EntailXY	0.154	0.001	0.004	0.010	0.000	0.154	0.001	1.000
5	EntailYX	0.013	0.001	0.000	0.001	0.000	0.013	0.001	1.000
6	Cramers V	0.042	0.006	0.003	0.008	0.001	0.149	0.006	0.995

Fig.10. Network relations test on RU 2007to2015 and IU 2015to2023

		1	2	3	4	5	6	7	8
		Obs Value	Significa	Average	Std Dev	Minimum	Maximum	Prop >= O	Prop <= O
1	Chi-Square	1165.652	0.012	60.051	415.564	0.344	8441.046	0.012	0.989
2	Correlation	0.033	0.001	-0.000	0.001	-0.000	0.033	0.001	1.000
3	Jaccard	0.010	0.001	0.000	0.000	0.000	0.010	0.001	1.000
4	EntailXY	0.011	0.001	0.000	0.000	0.000	0.011	0.001	1.000
5	EntailYX	0.089	0.001	0.002	0.004	0.000	0.089	0.001	1.000
6	Cramers V	0.012	0.012	0.001	0.003	0.000	0.033	0.012	0.989

Fig.11. Network relations test on IR 2007to2015 and IU 2015to2023

		1	2	3	4	5	6	7	8
		Obs Value	Significa	Average	Std Dev	Minimum	Maximum	Prop >= O	Prop <= O
1	Chi-Square	16614.656	0.001	61.787	619.048	0.304	16614.656	0.001	1.000
2	Correlation	0.013	0.001	0.000	0.001	-0.000	0.014	0.001	1.000
3	Jaccard	0.009	0.001	0.000	0.000	0.000	0.009	0.001	1.000
4	EntailXY	0.010	0.001	0.000	0.000	0.000	0.010	0.001	1.000
5	EntailYX	0.086	0.001	0.001	0.003	0.000	0.086	0.001	1.000
6	Cramers V	0.025	0.001	0.000	0.001	0.000	0.025	0.001	1.000

Fig.12. Network relations test on IUR 2007to2015 and IUR 2015to2023

Number of bootstrap samples: 3000
Variance of ties for ...IR2015to2023.##h: 0.0300
Variance of ties for ...IR2007to2015.##h: 0.0027
Classical standard error of difference: 0.0001
Classical t-test (indep samples): 25.4159
Estimated bootstrap standard error for density of ...IR2015to2023.##h: 0.0004
Estimated bootstrap standard error for density of ...IR2007to2015.##h: 0.0001
Bootstrap standard error of the difference (indep samples): 0.0004
95% confidence interval for the difference (indep samples): [0.0026, 0.0043]
bootstrap t-statistic (indep samples): 7.8602
Bootstrap SE for the difference (paired samples): 0.0004
95% bootstrap CI for the difference (paired samples): [0.0027, 0.0042]
t-statistic: 8.5721
Average bootstrap difference: 0.0034
Proportion of absolute differences as large as observed: 0.0003
Proportion of differences as large as observed: 0.0003
Proportion of differences as small as observed: 1.0000

Fig.13. IR network density test

Number of bootstrap samples: 5000
Variance of ties for ...UR2015to2023.##h: 0.0207
Variance of ties for ...UR2007to2015.##h: 0.0006
Classical standard error of difference: 0.0003
Classical t-test (indep samples): 25.2706
Estimated bootstrap standard error for density of ...UR2015to2023.##h: 0.0007
Estimated bootstrap standard error for density of ...UR2007to2015.##h: 0.0001
Bootstrap standard error of the difference (indep samples): 0.0007
95% confidence interval for the difference (indep samples): [0.0054, 0.0083]
bootstrap t-statistic (indep samples): 9.3019
Bootstrap SE for the difference (paired samples): 0.0007
95% bootstrap CI for the difference (paired samples): [0.0055, 0.0083]
t-statistic: 9.5412
Average bootstrap difference: 0.0069
Proportion of absolute differences as large as observed: 0.0002
Proportion of differences as large as observed: 0.0002
Proportion of differences as small as observed: 1.0000

Fig.14. UR network density test

Table 1 Basic data on distinct types of IUR collaborative networks in two consecutive periods

Time	Number of data items	Entities	Total participants	Total number of edges	Total number of nodes	Density
IU from 2007-06 to 2015-05	115	156	659	149	156	0.0123
IU from 2015-06 to 2023-05	969	1012	4799	1231	1012	0.0024
IR from 2007-06 to 2015-05	198	205	1005	190	205	0.0091
IR from 2015-06 to 2023-05	1611	1243	7229	1614	1243	0.0021
UR from 2007-06 to 2015-05	26	47	177	52	47	0.0481
UR from 2015-06 to 2023-05	521	511	2401	637	511	0.0049
IUR from 2007-06 to 2015-05	299	333	1548	303	333	0.0055
IUR from 2015-06 to 2023-05	2574	2107	11282	2588	2107	0.0012

Table 2 Key indicators for the four IUR networks over two consecutive periods

Key index	UR 2007 to 2015	IR 2007 to 2015	IU 2007 to 2015	IUR 2007 to 2015
# of nodes	47	205	156	333
# of ties	104	380	298	606
Avg Degree	2.213	1.854	1.91	1.82
Indeg H-Index	4	5	6	6
K-core index	3	3	3	3
Density	0.048	0.009	0.012	0.005
Components	12	64	41	98
Component Ratio	0.239	0.309	0.258	0.292
Avg Distance	2.578	2.652	3.46	3.211
SD Distance	1.390	1.192	1.864	1.612
Diameter	6	6	10	10
Key index	**UR 2015 to 2023**	**IR 2015 to 2023**	**IU 2015 to 2023**	**IUR 2015 to 2023**
# of nodes	511	1243	1012	2107
# of ties	1274	3228	2462	5176
Avg Degree	2.493	2.597	2.433	2.457
Indeg H-Index	12	15	16	19
K-core index	5	7	5	7
Density	0.005	0.002	0.002	0.001
Components	108	317	168	418
Component Ratio	0.211	0.254	0.165	0.198
Avg Distance	4.324	3.769	4.599	5.393
SD Distance	1.623	1.509	1.486	2.173
Diameter	13	10	10	17

Table 3 Top 10 assignees of distinct patent collaboration networks in two consecutive periods

Top 10 IU 15-23	Number	Top 10 IR 15-23	Number	Top 10 UR 15-23	Number	Top 10 IUR 15-23	Number
Tsinghua University	54	State Grid Corporation of China	215	Tsinghua University	58	State Grid Corporation of China	237
State Grid Corporation of China	50	Zhejiang Geely Holding Group Co.	105	State Grid Corporation of China	56	State Grid Corporation of China Limited	107
Shanghai Jiaotong University	38	State Grid Corporation of China Limited	104	Xi'an Jiaotong University	56	Zhejiang Geely Holding Group Co.	105
Southeast University	34	Zhejiang Geely Automobile Research Institute Co.	74	State Grid Corporation of China Limited	38	Tsinghua University	74
Xi'an Jiaotong University	34	Beijing Institute of Telemetry Technology	50	Shanghai Jiaotong University	36	Zhejiang Geely Automobile Research Institute Co.	74
Zhejiang University	26	China National Long March Rocket Technology Corporation (CGMRC)	50	Tsinghua University Suzhou Automotive Research Institute (Wujiang)	36	Beijing Institute of Telemetry Technology	50
State Grid Corporation of China Limited	22	China Electric Power Research Institute (CEPRI)	42	Sun Yat-sen University	34	China National Long March Rocket Technology Corporation (CGMRC)	50
North China Electric Power University	20	China Electric Power Research Institute Ltd.	40	Shunde, Guangdong Zhongshan University Carnegie Mellon University International Joint Research Institute	34	Xi'an Jiaotong University	46
Shandong University	20	State Grid Shanghai Electric Power Co.	37	China Electric Power Research Institute Ltd.	32	China Electric Power Research Institute (CEPRI)	43
Harbin Engineering University	19	China Petroleum and Chemical Corporation, Sinopec	32	Beijing University of Aeronautics and Astronautics	32	Shanghai Jiaotong University	42
Top 10 IU 07-15	**Number**	**Top 10 IR 07-15**	**Number**	**Top 10 UR 07-15**	**Number**	**Top 10 IUR 07-15**	**Number**
China National Offshore Oil Corporation	5	Zhejiang Geely Automobile Research Institute Co.	40	China National Offshore Oil Corporation	5	State Grid Corporation of China	48

Southwest Petroleum University	4	Zhejiang Geely Holding Group Co.	40	Southwest Petroleum University	4	Zhejiang Geely Automobile Research Institute Co.	40
State Grid Corporation of China	4	State Grid Corporation of China	38	State Grid Corporation of China	4	Zhejiang Geely Holding Group Co.	40
CNOOC Research Center	3	China Electric Power Research Institute (CEPRI)	12	CNOOC Research Center	3	Tsinghua University	15
Chinese University of Hong Kong	2	Zhejiang Geely Automobile Research Institute Co.	10	Chinese University of Hong Kong	2	China Electric Power Research Institute (CEPRI)	12
CNOOC Research Institute	2	China National Offshore Oil Corporation	8	Dalian University of Technology	2	Zhejiang Geely Automobile Research Institute Co.	10
Shanghai Jiaotong University	2	Beijing Institute of Telemetry Technology	8	Shanghai Jiaotong University	2	Shanghai Jiaotong University	9
Dalian University of Technology	2	China National Long March Rocket Technology Corporation (CGMRC)	8	CNOOC Research Institute	2	China National Offshore Oil Corporation	8
Xi'an Jiaotong University	2	China Petroleum and Chemical Corporation, Sinopec	5	Wuhan University	2	Beijing Institute of Telemetry Technology	8
China Electric Power Research Institute (CEPRI)	2	Commercial Aircraft Corporation of China Ltd.	5	Harbin Institute of Technology Shenzhen Graduate School	2	China National Long March Rocket Technology Corporation (CGMRC)	8
Chongqing University	2	State Grid Electric Power Research Institute Wuhan Nanrui Limited Liability Company	5	Guangdong Power Grid Corporation Electric Power Scientific Research Institute	2		
Wuhan University	2	CNOOC Research Center	5	Zhejiang Normal University	2		
Guangdong Power Grid Corporation Electric Power Scientific Research Institute	2	Michelin Research and Technology Ltd.	5	Chongqing University	2		
		Michelin Technology Inc.	5	Xi'an Jiaotong University	2		
		Nanjing Nanrui Group Company	5	China Electric Power Research Institute (CEPRI)	2		