



Innovation and Development Policy

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Evolution of Collaboration Network Structures and Influencing Factors of New R&D Institutions in the Yangtze River Delta Urban Agglomeration

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Abstract

Using collaborative patent data from 882 new R&D institutions in the Yangtze River Delta from 2011 to 2024, this paper examines how city-level industry-university-research collaboration networks have changed over time and what drives their formation. We map patent co-applications to city pairs, analyze the network using social network indicators, core-periphery analysis, and cohesive subgroup analysis, and then test the effects of multidimensional proximity using QAP correlation and regression models. Four findings stand out. First, the inter-city network expanded rapidly, while its density followed a V-shaped path. The structure became flatter, more accessible, and with increasingly small-world features. Second, the network shifted from an early point-to-point pattern to corridor-based growth, then to a denser, networked structure. Cities such as Hangzhou, Nanjing, Shanghai, and Hefei became important hubs, but differed sharply in their network functions. Third, the network retained a clear core-periphery pattern. A small number of cities formed a highly connected core, while many newly connected cities remained peripheral. Fourth, geographical, economic, and organizational proximity promoted collaboration, whereas institutional and technological proximity were negatively associated with tie formation. The findings suggest that new R&D institutions are not only local innovation actors but also relational platforms that reshape regional innovation networks. Policy should therefore combine support for core hubs with stronger mechanisms for cross-boundary resource sharing and integration with peripheral cities.

Keywords

New R&D institutions; Industry-university-research collaboration; Urban collaboration network; Yangtze River Delta; Social network analysis

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[10.20046/j.cnki.2096-5141.2026.0004](https://doi.org/10.20046/j.cnki.2096-5141.2026.0004)

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1. Introduction

A new wave of technological and industrial change has made collaborative innovation a basic condition for regional competitiveness. In China, the link between scientific research and industrial application has long been constrained by weak technology transfer, fragmented responsibilities, and uneven incentives among universities, firms, and research institutes (Zhou and Liu, 2018). Traditional point-to-point cooperation can solve individual technical problems, but it is often too loose to address system-level gaps in the innovation chain (Qiao and Liu, 2014). Scaling up the number of collaborative projects has proven insufficient on its own; what remains harder to achieve is the institutional architecture needed to link knowledge production, technology transfer, incubation, and industrial uptake within a functioning chain (Sun and Bi, 2021). Where universities, industries, and governments interact without surrendering their distinct functions (Etzkowitz, 2003), new organizational forms tend to emerge at the intersections – what Champenois and Etzkowitz (2018) call “intermediary organizations.” New R&D institutions represent one such form (Kanda *et al.*, 2019), and have attracted growing attention as connectors bridging the research and commercial sides of regional innovation systems.

Urban innovation capacity depends on the number of research actors present and how well they are connected to one another and to industrial demand. New R&D institutions are designed to straddle multiple functions, such as facilitating technology transfer and supporting incubation within a single organizational frame *et al.*. They have shaped urban innovation outcomes in the cities where they operate (Zhang *et al.*, 2024) by inserting themselves into the urban innovation chain (Mao *et al.*, 2024). The Yangtze River Delta offers a concentrated setting for examining this dynamic at scale. Cities in this region have advanced economy, fruitful research outputs and sophisticated industries. In 2021, it had a larger number of new R&D institutions than any other urban agglomeration, which makes it an excellent case to study how the new R&D institution collaboration networks evolve in a region.

So, this study constructs an urban collaboration network using collaborative patent data from 882 new R&D institutions in the Yangtze River Delta from 2011 to 2024, employs social network analysis to examine the network’s structural evolution patterns, and empirically tests mechanisms that influence multidimensional proximity factors. We try to provide empirical implications for optimizing regional innovation resource allocation and easing barriers to factor mobility, thereby supporting higher-quality, integrated development of the region.

2. Literature Review

2.1. Nature characteristics and innovation networks of new R&D institutions

The literature defines new R&D institutions from several angles, including their operating model, institutional flexibility, and position in the innovation chain (Zhou *et al.*, 2021; He, 2019). Although the terminology varies, four features are emphasized. First, their mission centers on linking technological innovation with industrial development (Wu and Yin, 2016). Second, their activities typically span several ranges of an innovation chain from research, technology transfer, incubation to industrial services (Zhang, 2017). Third, their governance is more market-oriented and flexible than that of conventional public research institutes (He, 2019). Fourth, their funding sources are usually diversified, combining public support, project income, enterprise investment, and service revenue (Zhang, 2017).

This paper treats new R&D institutions as independent legal entities that use diversified funding and

flexible governance arrangements to conduct research, promote technology transfer, support incubation, and connect stakeholders in the regional innovation system. Their value lies less in replacing existing actors than in reorganizing their relations. They create platforms for repeated interaction, reduce the distance between scientific knowledge and industrial demand, and help turn scattered resources into coordinated innovation activities.

From a knowledge-production perspective, new R&D institutions strengthen the backward linkage from industrial demand to research agendas and extend the forward linkage from research results to application (Shi, 2025). Relational contract theory views them as arrangements that stabilize cooperation among actors with different incentives (Ren, 2023). Strategic niche management emphasizes its role in providing protected spaces for experimentation and open innovation (Mi *et al.*, 2019). Network studies further show that such organizations can integrate resources, co-develop platforms, support knowledge exchange, and create non-redundant links among firms, universities, and research institutes (Ren, 2019), thereby enhancing overall efficiency through collaborative innovation that fills missing links (Sun and Bi, 2021; Mao *et al.*, 2021).

In practice, collaboration takes several forms, including technology equity arrangements, joint establishment, and talent exchange. Effective collaboration depends on alignment of interests, supported by clear intellectual property arrangements, fair benefit sharing, and appropriate compensation for R&D risks (Wang *et al.*, 2016). Improving collaboration efficiency necessitates refining the collaboration mechanism, strengthens “self-sustaining capacity,” and expands cross-boundary innovation (Ren, 2019).

2.2. A review of studies on industries, universities, and research institutes collaboration networks

Research on industry–university–research collaboration networks has mainly developed along three lines. The first focuses on network structure and evolution. Studies commonly use social network analysis to examine their density, centrality, clustering, structural holes, small-world characteristics (Pinto *et al.*, 2019), and scale-free features (Basole, 2016), thereby revealing whether collaboration networks are hub-dominated, broker-dependent, or locally clustered yet externally connected (Wu *et al.*, 2020).

The second line examines the factors shaping collaboration. Multidimensional proximity—including geographical, technological, economic, institutional, and linguistic proximity—has become a key explanatory framework (Xu and Wu, 2019), though its effects may differ across innovation stages (Hu and Li, 2017). Other factors include knowledge transfer (Watts, 1989), tie strength, network range, cohesion, heterogeneity (Reagans and McEvily, 2003), organizational attributes, relational ties, and external environments (Xiao and Zhu, 2013). From related perspectives, uncertainty, specific investment, coordination costs (Huang, 2015), firm size, government support, regional economic development (Huang, 2017), technological, structural, and environmental conditions (Yao *et al.*, 2017), functional complementarity, knowledge spillovers, market pull, and government drive have also been identified as important drivers (Yang *et al.*, 2019). At the city level, firms are viewed as “city network makers” because their intercity economic interactions and knowledge flows help shape urban innovation networks (Taylor, 2001; Wen *et al.*, 2021). However, although policy effects of new R&D institutions on urban innovation have been discussed (Mao *et al.*, 2024), less attention has been paid to how these institutions themselves participate in and reshape intercity collaboration networks.

The third line concerns the research scale. At the macro-regional level, studies have examined urban agglomerations such as the Middle Yangtze River, Chengdu–Chongqing, Beijing–Tianjin–Hebei, the Bohai Rim, and the Pearl River Delta (Tang and Chai, 2022; Ma and Xu, 2023; Zuo *et al.*, 2025). At the meso-industrial level, research has focused on strategic emerging industries, including integrated circuits,

intelligent manufacturing equipment, graphene, and artificial intelligence (Su *et al.*, 2023; Tao *et al.*, 2025). At the micro-actor level, studies have explored the roles and interactions of universities, firms, and traditional research institutes within broader industry–university–research collaboration networks (Basso *et al.*, 2021; Zhang *et al.*, 2025).

Three gaps nonetheless persist. Existing studies still focus mainly on traditional actors, offer limited evidence on how new R&D institutions reshape city-level collaboration structures, and provide insufficient explanation of the mechanisms behind their intercity networks. This paper addresses these gaps by combining social network analysis with QAP models.

3. Research Design

3.1. Data

Patent data are widely used to identify collaboration networks and trace knowledge flows among innovation actors. This study uses jointly applied patents as an indicator of industry–university–research collaboration among new R&D institutions, universities, research institutes, and firms. The dataset includes invention, utility, and design patents.

The data covers the Yangtze River Delta, comprising three provinces (Jiangsu, Zhejiang, and Anhui) and Shanghai municipality. We collect lists of officially accredited new R&D institutions from government websites, policy documents, and official announcements, and cross-check each entry against institutional websites, public reports, and media sources. Then, we use both their current names and previous names for patent retrieval, merge the duplicates and then remove those that have been deregistered or stripped of accreditation. Finally, we get a list of 882 institutions.

We retrieve the patent data from the AI Pat+ Patent System. The retrieval window spans 2011 to 2024. Records from 2025 were excluded as that year was still incomplete at the time of collection. From the raw returns, we remove patents with lapsed status, filings attributed solely to individual applicants and the patents that did not reflect cross-type organizational collaboration. Following verification, 24,354 collaborative patents remained. To support longitudinal analysis, the study period was divided into 2011–2015, 2016–2020, and 2021–2024.

For the QAP analysis, the temporal scope of 2019–2023 is narrower. Observations prior to 2019 were dropped because the network was still too sparse to yield stable regression estimates. The endpoint reflects a practical constraint. 2023 is the latest year for which comparable statistical data is available across all sources. The urban collaboration matrix and technological proximity measures are drawn from AI Pat+; geographic proximity is calculated using city coordinates obtained from GeoNames. The remaining variables are drawn from the China Statistical Yearbook, the China Urban Statistical Yearbook, and provincial statistical yearbooks.

3.2. Network construction and indicators

The analysis maps patent co-application data to the city level by assigning each applicant organization to its home city, producing a city-pair collaboration matrix. Working at the city scale rather than the individual institution allows structural patterns to emerge at the level most meaningful for regional innovation governance (Fig. 1). Then, we use the social network metrics to characterize the city positions in the network, connection intensities, and brokerage role (Table 1).

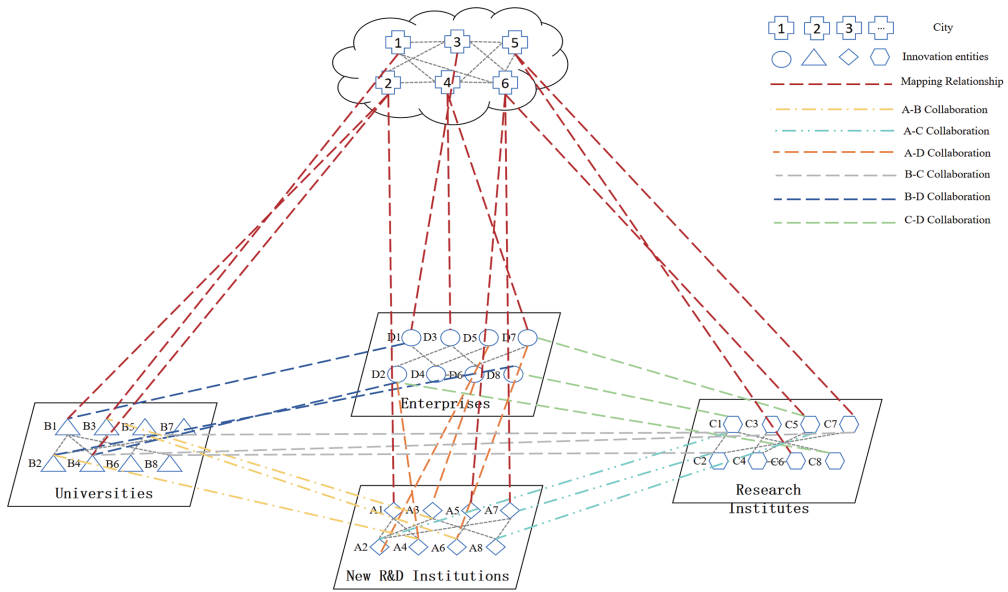


Fig. 1. Mapping the relationship between industries, universities, and research institute collaboration networks.

Table 1
Network structural characteristic metrics.

Metric Names	Calculation Formulas	Parameter Descriptions
Network Density	$D = \frac{2m}{N(N-1)}$	D denotes network density, m represents the actual number of relationships within the network, and n denotes the number of nodes present in the network
Average Degree	$AD = \frac{\sum_i \sum_j X_{ij}}{n}$	AD denotes average degree, $\sum_i X_{ij}$ represents the number of nodes connected to node i , and n is the total number of nodes
Network Centralization	$C = \frac{\sum_{i=1}^n (C_{max} - C_i)}{\max[\sum_{i=1}^n (C_{max} - C_i)]}$	C denotes centralization, C_{max} represents the maximum value of centralization among all nodes in the network, and C_i denotes the centralization of node i
Average Path Length	$AL = \frac{\sum_{i \neq j} L_{ij}}{n(n-1)}$	AL denotes the average path length, and L_{ij} represents the shortest path length between node i and node j
Average Clustering Coefficient	$C_i = \frac{1}{n} \sum_{i \in N} \frac{2E_i}{n_i(n_i-1)}$	C_i denotes the average clustering coefficient, where n_i represents the number of nodes connected to i ; E_i denotes the sum of the actual number of edges existing between these n nodes connected to i
Degree Centrality	$C_{D_i} = \sum_{j \in N} x_{ij}$	C_{D_i} denotes degree centrality, where x_{ij} represents the connection between node i and node j . The value is 1 if a connection exists, and 0 otherwise
Betweenness Centrality	$C_{B_i} = \sum_{j \in N} \sum_{k \in N} \frac{g_{jk}(i)}{g_{jk}}$	C_{B_i} denotes betweenness centrality, where g_{jk} represents the number of shortest paths between node j and node k ; $g_{jk}(i)$ denotes the shortest path between node j and node k that passes through node i
Closeness Centrality	$C_{c_i} = \frac{1}{\sum_{j \in N} d_{ij}}$	C_{c_i} denotes closeness centrality, while d_{ij} represents the distance between node i and node j
Structural Holes	$C_{ij} = (p_{ij} + \sum_q p_{ij} p_{iq})^2$	C_{ij} denotes the structural hole, while p_{iq} represents the proportion of relationships invested in q out of all relationships at node i

4. Spatial Evolution of Collaborative Patent Output

Based on the data, intercity collaborative patents increased substantially from 2011 to 2024, rising from 225 to 8,395. This growth indicates that new R&D institutions have become increasingly important in promoting cross-organizational collaboration and regional innovation output (Fig. 2). Spatially, the network evolved from a scattered multi-point pattern in the first stage to a clearer core-periphery structure in the second stage, with a high-density belt emerging along the Nanjing-Shanghai-Hangzhou axis. In the third stage, collaboration became further concentrated in a few core cities, showing a stronger Matthew effect. Hangzhou remained the leading city throughout the three stages, while cities in northern Jiangsu, southwestern Zhejiang, and northern Anhui stayed relatively peripheral.

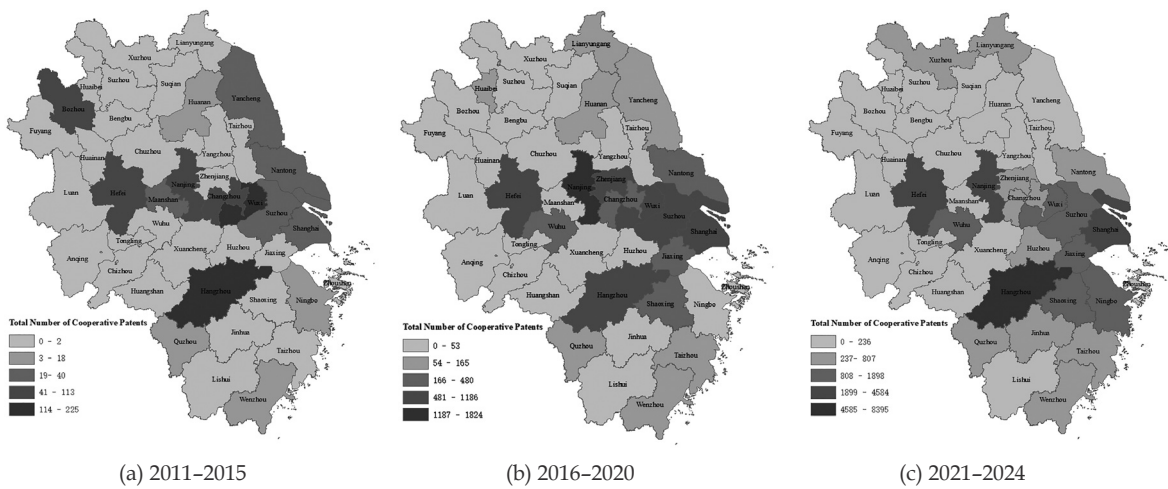


Fig. 2. Number of collaborative patents in the Yangtze River Delta region.

5. Inter-city Patent Collaboration Network Analysis

5.1. Overall characteristic evolution

Table 2 presents four evolutionary characteristics of the inter-city collaboration network.

First, the number of cities participating in collaborations among industries, universities, and research institutes has grown substantially (from 24 to 202). Collaborative ties between cities have become exceptionally dense, and the scale and interconnectedness of collaboration among new R&D institutions have developed rapidly. More cities are being integrated into the innovation network, and their collaborative links grow closer.

Second, network density shows a V-shaped pattern. It drops from 0.200 in 2011-2015 to 0.132 in 2016-2020, and then rebound to 0.259 in 2021-2024. The high density in the early period indicates that the network is small and mainly consisted of point-to-point collaborations among geographically close participants. When more cities and new R&D institutions join the network, the rapid expansion of nodes outpaces the establishment of stable collaboration links. It results in lower density. In the latest phase, nevertheless, existing institutions have built greater capacity and mutual trust. Meanwhile,

regional integration has lowered collaboration barriers, making the network denser and more interconnected.

Third, the network becomes flatter and more accessible. Degree centrality declines first and then rose, but it remained at a relatively low level overall. This suggests that the network has not evolved into a highly centralized star-shaped structure controlled by a small number of cities. Betweenness centrality decreases steadily, showing less reliance on intermediary nodes. As the structure becomes flatter and more decentralized, the overall collaboration efficiency is improved. The continuous growth of proximity centrality means the average topological distance among network cities is shrinking. Accordingly, the network achieves better overall accessibility and operational efficiency.

Fourth, the network displays distinct small-world properties. Its average clustering coefficient stays high, which reveals that the network contains many closely connected subgroups and collaborations tend to form cliques. The average path length drops from 2.542 to 1.833, meaning any two cities in the network can be connected via fewer than two intermediate links on average. Such a structure enables the efficient flow of information, knowledge and resources. In line with the widely recognized criteria for small-world networks (average clustering coefficient >0.1 and average path length <10) (Valverde *et al.*, 2002), the collaboration network exhibits small-world characteristics in all three periods.

Table 2

Overall characteristics of the urban network in the Yangtze River Delta region.

Metrics	2011-2015	2016-2020	2021-2024
Network scale	16	36	40
Number of relationships in the network	24	83	202
Network Density	0.2	0.132	0.259
Average Degree	3	4.611	10.1
Degree Centralization	0.069	0.05	0.115
Betweenness Centralization	0.380	0.328	0.204
Closeness Centralization	0.327	0.494	0.564
Average Clustering Coefficient	0.6	0.498	0.642
Average Path Length	2.542	2.286	1.833

To more clearly show the spatial evolution of the collaboration network, this study maps the network across three stages (Fig. 3). From 2011 to 2015, the network was in an early “point-axis” stage, with sparse and weak ties mainly concentrated between geographically adjacent cities. From 2016 to 2020, it entered a “corridor-based” stage, as both intra-provincial ties and cross-provincial collaboration expanded, forming several important corridors of collaboration. From 2021 to 2024, the network became denser, multi-centered, and fully networked. Several high-intensity urban clusters emerged, and the overall structure showed a clear core-periphery pattern, with collaboration intensity declining from core cities such as Shanghai, Nanjing, Hangzhou, Hefei, Shaoxing, and Ningbo toward the periphery.

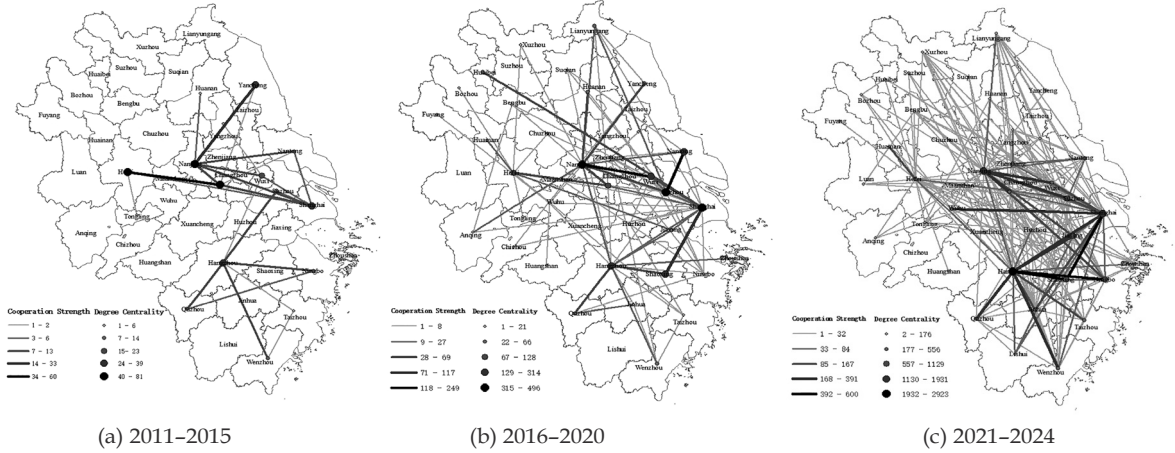


Fig. 3. Spatial distribution of collaboration networks in the Yangtze River Delta region.

5.2. Individual trait evolution

Table 3
Individual characteristics of urban networks (Top 10) 2011-2015.

City	Degree Centrality		Betweenness Centrality		Closeness Centrality		Structural Holes		
	Value	Rank	Value	Rank	Value	Rank	Effective Size	Constraint	Constraint Ranking
Changzhou	81	1	6.5	7	8.667	5	4.246	0.63	7
Nanjing	76	2	27.833	4	9.667	2	5.574	0.307	2
Hefei	65	3	14	5	7.5	7	2.068	0.91	8
Hangzhou	39	4	49	1	9.417	3	5.536	0.293	1
Yancheng	34	5	0	8	6.833	9	1.846	0.969	10
Shanghai	34	6	33.667	3	9.833	1	4.935	0.512	4
Wuxi	23	7	43.167	2	9.333	4	3.505	0.496	3
Nantong	14	8	0	8	7.5	8	2.185	0.625	6
Suzhou	14	9	10.833	6	7.833	6	2	0.592	5
Ningbo	12	10	0	8	6.45	10	1.067	1.011	14

Table 3 shows the individual network characteristics for 2011-2015. In terms of degree centrality, Changzhou, Nanjing, and Hefei formed the first tier, indicating that a few active cities drove early collaboration. Changzhou had the largest number of direct ties, but its role as an intermediary was limited. By contrast, Hangzhou, Wuxi, and Shanghai ranked higher in betweenness centrality, suggesting stronger control over knowledge and resource flows. Shanghai, Nanjing, and Hangzhou also showed high closeness centrality, meaning they could reach other cities more efficiently. In terms of structural holes, Hangzhou, Nanjing, and Wuxi held more advantageous positions, gaining access to non-redundant information and brokerage benefits. Overall, the early network was decentralized: Changzhou acted as a direct collaboration hub, while Shanghai, Hangzhou, and Wuxi played stronger intermediary and resource-control roles.

Table 4
Individual characteristics of urban networks (Top 10) 2016–2020.

City	Degree Centrality		Betweenness Centrality		Closeness Centrality		Structural Holes		
	Value	Rank	Value	Rank	Value	Rank	Effective Size	Constraint	Constraint Ranking
Nanjing	496	1	108.294	4	24.5	2	13.717	0.306	6
Suzhou	361	2	31.253	7	22.167	4	8.757	0.574	16
Shanghai	352	3	211.937	1	27	1	17.586	0.277	2
Wuxi	314	4	5.719	13	19	10	5.443	0.585	18
Nantong	288	5	4.783	14	18.5	11	3.337	0.826	24
Hangzhou	214	6	132.723	2	23.833	3	12.68	0.287	3
Shaoxing	184	7	0	24	16.833	18	1.836	0.583	17
Changzhou	128	8	12.126	10	20	8	5.155	0.374	8
Hefei	103	9	123.662	3	21.833	5	10.749	0.287	3
Quzhou	66	10	1.033	21	15.75	25	2.525	0.603	19

The individual characteristics of the urban network from 2016 to 2020 are presented in Table 4. Regarding degree centrality, Nanjing replaced Changzhou as the most pivotal direct connection hub within the network, with its value increasing by an order of magnitude. Along with Suzhou and Shanghai, Nanjing constituted the core of the network. Changzhou's relative standing declined sharply, with the network's center of gravity rapidly concentrating towards Nanjing, Shanghai, and Suzhou, while the network's scale continued to expand. Regarding betweenness centrality, Shanghai ranked first, followed closely by Hangzhou and Hefei, indicating that Shanghai not only increased its direct connections but also strengthened its control over the flow of innovation resources across the entire region, becoming a crucial bridge within the network. In terms of closeness centrality, Shanghai and Nanjing exhibited high values, making them the most accessible hubs within the network and capable of interacting most effectively with other parts of the network.

Regarding structural holes, Shanghai, Hangzhou, and Hefei exhibit relatively low degree centrality and relatively large effective size, occupying advantageous network positions. At this stage, Nanjing and Shanghai emerge as the two relatively important core cities within the network. Cities such as Hangzhou and Hefei are rapidly rising as secondary hubs, while earlier active cities like Changzhou are becoming relatively marginalized, reflecting a trend of regional innovation resources concentrating in higher-tier cities.

Table 5
Individual characteristics of urban networks (Top 10) 2021–2024.

City	Degree Centrality		Betweenness Centrality		Closeness Centrality		Structural Holes		
	Value	Rank	Value	Rank	Value	Rank	Effective Size	Constraint	Constraint Ranking
Hangzhou	2923	1	59.411	4	31	3	21.289	0.223	3
Shanghai	1931	2	60.656	3	31	4	20.787	0.286	4
Nanjing	1524	3	163.793	1	35	1	28.795	0.221	2
Shaoxing	1129	4	8.819	11	27	10	10.54	0.593	26

Table 5. (continued)

City	Degree Centrality		Betweenness Centrality		Closeness Centrality		Structural Holes		
	Value	Rank	Value	Rank	Value	Rank	Effective Size	Constraint	Constraint Ranking
Ningbo	996	5	16.83	8	29	7	12.417	0.625	29
Jiaxing	741	6	18.911	7	27.5	9	9.999	0.556	23
Suzhou	624	7	28.092	6	29.5	5	15.044	0.377	7
Wuxi	556	8	40.096	5	29	6	13.481	0.528	21
Hefei	521	9	153.662	2	31.5	2	21.969	0.211	1
Changzhou	441	10	4.378	17	26	12	8.864	0.634	30

Table 5 presents the individual network characteristics for 2021–2024. Hangzhou ranks first in degree centrality and becomes the city with the most direct collaborative ties. In terms of betweenness centrality, Nanjing and Hefei become the main bridging nodes, indicating their growing role in connecting sub-networks and supporting cross-regional collaboration. Nanjing, Hefei, and Hangzhou rank high in closeness centrality, suggesting strong accessibility within the network. In terms of structural holes, Hefei, Nanjing, and Hangzhou occupy advantageous positions, with more non-redundant connections and lower constraints. Overall, the Yangtze River Delta have formed a multi-centered collaboration network led by Hangzhou, Nanjing, Hefei, and Shanghai.

To further classify city roles, this study uses the average values of degree centrality and betweenness centrality as benchmarks. Cities are divided into four types: high-importance/high-coordination (H-H), high-importance/low-coordination (H-L), low-importance/high-coordination (L-H), and low-importance/low-coordination (L-L). H-H cities have both frequent direct ties and strong bridging capacity; H-L cities are well connected but have weaker coordination roles; L-H cities have fewer ties but still play brokerage roles; and L-L cities remain weak in both connection breadth and coordination capacity. The classification results are shown in Table 6.

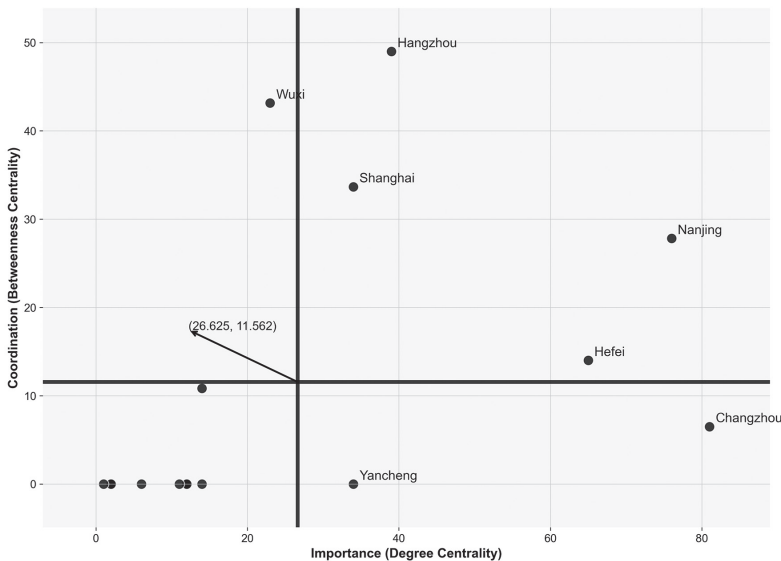


Fig. 4. Characteristic classification of urban node types (2011-2015).

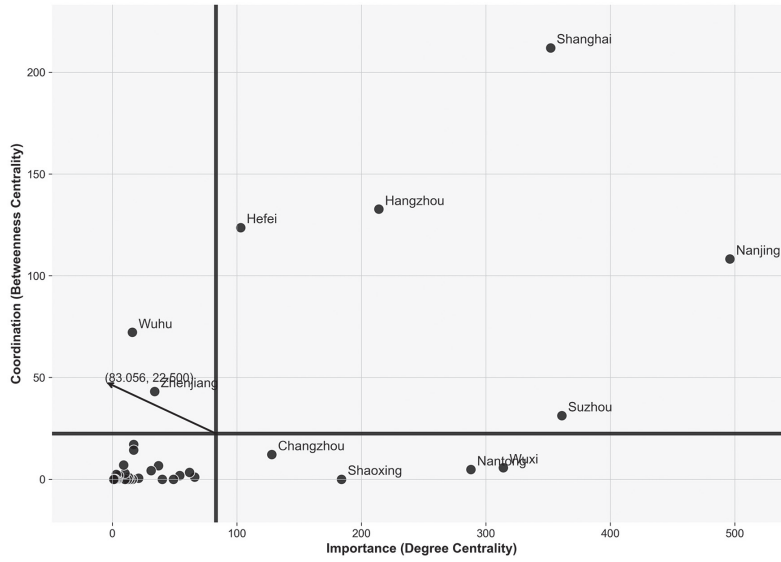


Fig. 5. Characteristic classification of urban node types (2016-2020).

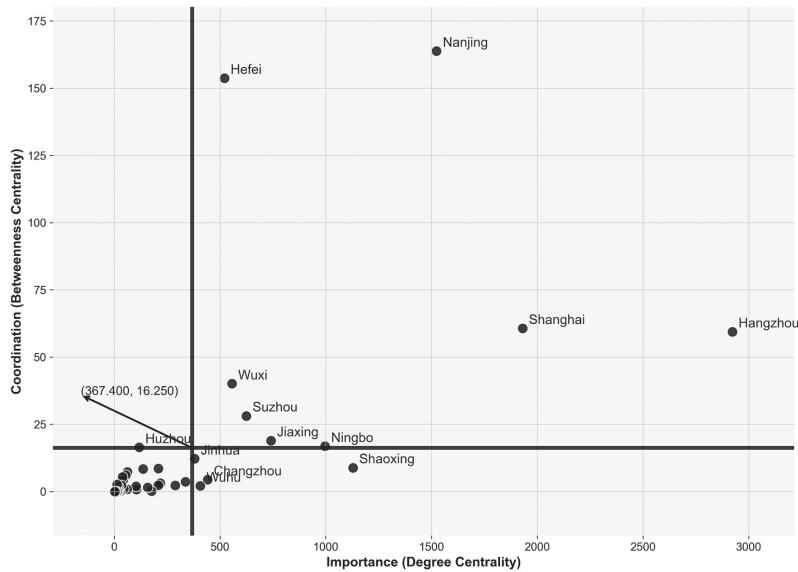


Fig. 6. Characteristic classification of urban node types (2021-2024).

In the initial stage, Nanjing, Hefei, Hangzhou, and Shanghai were classified as H-H cities and played key roles in the network. Suzhou joined this group in the second stage, and by the third stage, more cities such as Ningbo and Jiaxing had also become H-H cities, reflecting the expansion of the network core.

H-L cities, such as Changzhou and Shaoxing, maintained many direct ties but had weaker coordination capacity. L-H cities, including Zhenjiang, Wuhu, and Huzhou, had fewer connections but still played bridging roles in specific local or sectoral contexts. L-L cities remained peripheral, with weak connectivity and limited coordination capacity. Their number increased from nine to twenty-seven, indicating persistent unevenness in the regional collaboration network.

Some cities also moved upward in the network hierarchy. Suzhou, Ningbo, and Jiaxing gradually shifted from L-L to H-H cities, showing their growing influence in regional collaboration. This transition reflects the deepening of the Yangtze River Delta integration and the gradual improvement of regional collaborative innovation mechanisms.

Table 6

Characteristics of node types in the urban collaboration network of the Yangtze River Delta region.

Time Period	Type	Number	City Name
2011-2015	H-H	4	Nanjing, Hefei, Hangzhou, Shanghai
	H-L	2	Changzhou, Yancheng
	L-H	1	Wuxi
	L-L	9	Nantong, Suzhou, Ningbo, Quzhou, Wenzhou, Huaian, Yangzhou, Taizhou, Tongling
2016-2020	H-H	5	Nanjing, Suzhou, Shanghai, Hangzhou, Hefei
	H-L	4	Wuxi, Nantong, Shaoxing, Changzhou
	L-H	2	Zhenjiang, Wuhu
	L-L	25	Quzhou, Jiaxing, Yancheng, Huaibei, Huaian, Wenzhou, and 20 other cities (25 cities in total)
2021-2024	H-H	8	Hangzhou, Shanghai, Nanjing, Ningbo, Jiaxing, Suzhou, Wuxi, Hefei
	H-L	4	Shaoxing, Changzhou, Wuhu, Jinhua
	L-H	1	Huzhou
	L-L	27	Wenzhou, Quzhou, Nantong, Taizhou, Zhenjiang, Lishui, and 21 other cities (27 cities in total)

5.3. Core-periphery structures

Table 7

Analysis of the core-periphery structure in the urban collaboration network of the Yangtze River Delta region.

Time Period	Core Block	Periphery Block	Core Block Density	Core-Periphery Density	Periphery Block Density
2011-2015	Wuxi, Hangzhou, Hefei, Changzhou, Yancheng, Shanghai, Nanjing, Huaian, Suzhou, Nantong, Tongling	Taizhou, Wenzhou, Yangzhou, Quzhou, Ningbo	3.255	0.527	0.5
2016-2020	Jiaxing, Shanghai, Wuxi, Nanjing, Suzhou, Hangzhou, and 8 other cities (14 cities in total)	Ningbo, Wuhu, Maanshan, Taizhou, Wenzhou, Anqing, and 16 other cities (22 cities in total)	13.044	0.756	0.325
2021-2024	Jiaxing, Shanghai, Ningbo, Hangzhou, Shaoxing	Nanjing, Taizhou, Suzhou, Yangzhou, Wuhu, Maanshan, Hefei, and 28 other cities (35 cities in total)	252.1	15.303	3.612

Table 7 shows a clear core-periphery structure in the Yangtze River Delta collaboration network. From 2011 to 2015, the core included 11 cities, while only 5 cities were in the periphery. Core cities are already more closely connected, as shown by their higher internal density. Peripheral cities, by contrast, have weak ties both among themselves and with the core.

From 2016 to 2020, more cities entered the network, and the number of core and peripheral cities increased to 14 and 22, respectively. The core became more cohesive, with its internal density rising sharply, while peripheral cities remained relatively isolated, which suggests that network expansion does not immediately bring balanced integration.

From 2021 to 2024, the core area shrank notably while becoming far denser. Only Jiaxing, Shanghai, Ningbo, Hangzhou and Shaoxing stayed in the core, forming a tightly connected cluster. Meanwhile, the peripheral group expanded to 35 cities. Though connections among peripheral cities remained relatively weak, their ties with the core and with each other were strengthened.

Overall, the network evolves toward a small core and large periphery structure. The core threshold becomes higher, meaning that only cities with the strongest and most frequent ties remains in the core. The movement of cities such as Nanjing, Hefei, Suzhou, Wuxi, and Changzhou from core to periphery does not necessarily indicate decline; rather, it reflects the growing concentration of strong ties among a smaller number of cities. At the same time, the expanding periphery indicates that the collaboration network is covering more cities, though many remain only loosely integrated.

5.4. Cohesive subgroups

Cohesive subgroups are identified using the Concor analysis module within UCINET software was utilized, with a maximum segmentation depth of 2 and a convergence criterion of 0.2. Cities across the Yangtze River Delta region were uniformly partitioned into four clusters during each period. Subsequently, ArcGIS 10.8 tools were applied to analyze their spatial clustering properties. The detailed partitioning results are presented in Table 8.

Table 8

Blockmodel classification of the urban collaboration network in the Yangtze River Delta region.

Time Period	Subgroup	Number	City Name
2011-2015	Subgroup I	7	Wuxi, Changzhou, Hefei, Huaian, Yancheng, Nantong, Nanjing
	Subgroup II	3	Yangzhou, Shanghai, Tongling
	Subgroup III	1	Hangzhou
	Subgroup IV	5	Suzhou, Taizhou, Wenzhou, Quzhou, Ningbo
2016-2020	Subgroup I	9	Jiaxing, Huainan, Tongling, Taizhou, Xuzhou, Wuhu, Maanshan, Bozhou, Chuzhou
	Subgroup II	6	Jinhua, Wenzhou, Zhoushan, Huangshan, Fuyang, Quzhou
	Subgroup III	13	Huaian, Lianyungang, Nanjing, Wuxi, Shanghai, Ningbo, Changzhou, Suqian, Zhenjiang, Nantong, Taizhou, Yancheng, Suzhou
	Subgroup IV	8	Huzhou, Anqing, Huaibei, Bengbu, Chizhou, Hefei, Shaoxing, Hangzhou

Table 8. (continued)

Time Period	Subgroup	Number	City Name
2021-2024	Subgroup I	16	Jiaxing, Wenzhou, Lishui, Nanjing, Ningbo, Wuxi, Suqian, Huzhou, Taizhou, Hangzhou, Suzhou, Jinhua, Xuzhou, Shaoxing, Quzhou, Zhoushan
	Subgroup II	10	Nantong, Huaian, Lianyungang, Shanghai, Yancheng, Changzhou, Chuzhou, Taizhou, Zhenjiang, Yangzhou
	Subgroup III	10	Lu'an, Tongling, Bozhou, Huaibei, Fuyang, Suzhou, Bengbu, Anqing, Huainan, Huangshan
	Subgroup IV	4	Hefei, Maanshan, Wuhu, Xuancheng

As shown in Table 8 and Fig. 7, the subgroup structure also changed over time. From 2011 to 2015, each subgroup contains only a few cities, and the grouping is mainly shaped by geographical proximity. Cities tend to collaborate with nearby cities, showing a clear local clustering pattern.

From 2016 to 2020, the subgroups become larger, and core cities such as Shanghai and Nanjing begin to play a stronger role in connecting different areas, which suggests that the network was entering a stage of faster consolidation. At the same time, differences between subgroups have become more pronounced, with some groups composed mainly of peripheral cities.

From 2021 to 2024, geographical clustering became even clearer. Although some cities cross provincial boundaries in their collaborations, neighboring cities still tend to be grouped together. One subgroup consisted mainly of cities in Zhejiang, another centered on cities in Jiangsu, while the remaining two are largely associated with cities in Anhui Province.

To further examine the strength of ties within and between subgroups, this study uses density matrices. The overall network density is used as the threshold: values above the threshold are coded as 1, and values below it are coded as 0. The results are shown in Tables 9, 10, and 11.

Table 9

Density matrix and image matrix of subgroup relations (2011–2015).

Subgroup	Density Matrix				Image Matrix			
	Subgroup I	Subgroup II	Subgroup III	Subgroup IV	Subgroup I	Subgroup II	Subgroup III	Subgroup IV
Subgroup I	0.381	0.333	0.143	0	1	1	0	0
Subgroup II	0.333	0	0	0.067	1	0	0	0
Subgroup III	0.143	0	0	1	0	0	0	1
Subgroup IV	0	0.067	1	0.2	0	0	1	1

The density and image matrices in Table 9 show the 2011–2015 network divided into two largely independent clusters. Subgroups I and II exchanged ties with each other and maintained some internal cohesion; Subgroups III and IV did the same. Across this divide, however, the two clusters had no meaningful contact – the off-diagonal image matrix values between those pairings are uniformly zero. Geography goes

some way toward explaining the pattern: Subgroups I and II drew predominantly on cities in the northern Yangtze River Delta, while Subgroups III and IV were anchored in the south. During this period, collaboration operated largely within two distinct geographic bands, with no bridging ties between them.

By 2016–2020, the subgroup structure had grown more complex (Table 10). Subgroup III now stood out as the most internally cohesive, with a density of 0.397 – markedly higher than any other subgroup – and encompassed the largest number of cities. Subgroup IV, though internally looser, had taken on a bridging function, registering above-threshold ties to both Subgroup I and Subgroup III; it played a connective role the first-period clusters had lacked. As the Yangtze River Delta integration strategy gathered momentum during these years, cities across Subgroups I, III, and IV increasingly pulled into a single, denser interaction zone. Subgroup II stood apart from this consolidation: its cities exchanged ties mainly with one another and had no above-threshold connections to any other subgroup, suggesting the broader integration dynamic had not yet reached that cluster.

Table 10

Density matrix and image matrix of subgroup relations (2016–2020).

Subgroup	Density Matrix				Image Matrix			
	Subgroup I	Subgroup II	Subgroup III	Subgroup IV	Subgroup I	Subgroup II	Subgroup III	Subgroup IV
Subgroup I	0	0.056	0.068	0.181	0	0	0	1
Subgroup II	0.056	0.133	0.026	0.083	0	1	0	0
Subgroup III	0.068	0.026	0.397	0.173	0	0	1	1
Subgroup IV	0.181	0.083	0.173	0.071	1	0	1	0

Table 11

Density matrix and image matrix of subgroup relations (2021–2024).

Subgroup	Density Matrix				Image Matrix			
	Subgroup I	Subgroup II	Subgroup III	Subgroup IV	Subgroup I	Subgroup II	Subgroup III	Subgroup IV
Subgroup I	0.625	0.281	0.094	0.297	1	1	0	1
Subgroup II	0.281	0.467	0.04	0.075	1	1	0	0
Subgroup III	0.094	0.04	0.067	0.325	0	0	0	1
Subgroup IV	0.297	0.075	0.325	0.667	1	0	1	1

The 2021–2024 period saw two dominant internal cores emerge (Table 11). With densities of 0.625 and 0.667, respectively, Subgroups I and IV are considerably more cohesive than the other two; Subgroup III in particular is internally sparse, falling below the image matrix threshold. Subgroup II, while internally coherent, connects outward only to Subgroup I. Subgroup III links only to Subgroup IV. The two cores are also directly tied to each other, forming a structure in which I and IV anchor the network, while II and III each attach to one or the other. Compared with the preceding period, cities within each subgroup had grown more tightly bound, and the ties running between subgroups continued to follow geographical proximity rather than crossing the spatial gaps that the network had not yet bridged (Fig. 7).

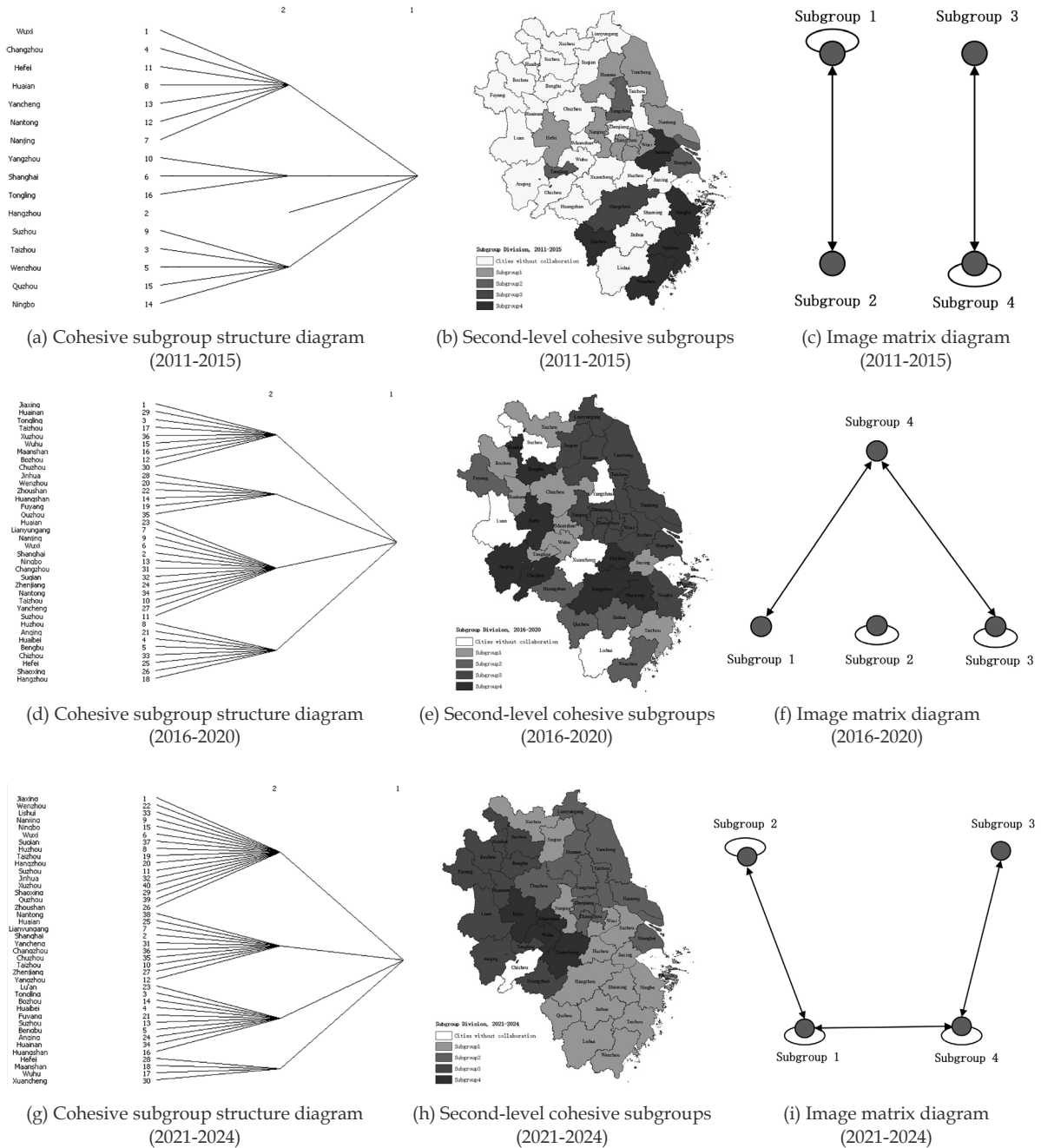


Fig. 7. Cohesive subgroups of the network across three time periods.

6. Factors Influencing the Urban Collaboration Network

6.1. Variables and measurement

6.1.1. Dependent variable

This study investigates the mechanism by which multidimensional proximity influences the evolution of

urban collaboration networks. By taking the collaboration among industries, universities, and research institutes as the micro-level analytical unit, this study constructs a binary relationship matrix to represent the regional urban collaboration network. Specifically, collaborative relationships between nodes are binarised to analyze the impact of multidimensional proximity on the structural evolution of urban networks. A collaboration relationship between two cities is deemed to exist if they have jointly applied for a relevant patent; otherwise, it is assigned a value of 0. Based on this approach, a relationship matrix for the urban collaboration network in the Yangtze River Delta was constructed, encompassing data spanning multiple years.

6.1.2. Multidimensional proximity

(1) Geographical proximity

Following Hong and Su (2013), geographical distance between cities is calculated between city i and city j using the following formula:

$$dist_{ij} = 6371 * \{ \arccos[\sin(lat_i) \sin(lat_j) + \cos(lat_i) \cos(lat_j) \cos(|long_i - long_j|)] \} \quad (1)$$

In the formula, $dist_{ij}$ denotes the geographical distance between two cities; lat_i and lat_j represent the latitudes of cities i and j , respectively; $long_i$ and $long_j$ denote the longitudes of the two cities, respectively; the constant 6371 (kilometers) is the Earth's mean radius.

The raw distance values are then rescaled to a $[0, 1]$ interval using min-max normalization:

$$Geo_{ij} = \frac{Max(dist_{ij}) - dist_{ij}}{Max(dist_{ij}) - Min(dist_{ij})} \quad (2)$$

Where Geo_{ij} is the geographical proximity score for the city pair (i, j) . The inversion means that geographically close pairs score close to 1 and distant pairs score close to 0. These scores populate the $m \times m$ geographical proximity matrix G .

$$G = \begin{bmatrix} g_{11}(t) & \cdots & g_{1m}(t) \\ \vdots & \ddots & \vdots \\ g_{m1}(t) & \cdots & g_{mm}(t) \end{bmatrix} \quad (3)$$

(2) Institutional Proximity

Institutional proximity is operationalized using administrative rank. Following Zhou (2025), a city pair is assigned a value of 1 if both cities share the same administrative tier and 0 if they differ – on the basis that cities at equivalent ranks face broadly comparable regulatory environments, making collaboration administratively less costly:

$$INST_{ij} = \begin{cases} 1, & \text{if cities } i \text{ and } j \text{ share the same administrative tier} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

These values populate the $m \times m$ institutional proximity matrix $INST$:

$$INST = \begin{bmatrix} inst_{11}(t) & \cdots & inst_{1m}(t) \\ \vdots & \ddots & \vdots \\ inst_{m1}(t) & \cdots & inst_{mm}(t) \end{bmatrix} \quad (5)$$

(3) Economic proximity

Economic proximity captures the degree to which two cities operate at comparable economic scales. Following Duan *et al.* (2018), a city pair is coded 1 if both cities have regional GDP above the sample mean, and 0 if either falls below it. This binary specification targets high-capacity pairings – the configurations most likely to support research-intensive collaboration – while remaining tractable given available data.

$$E_{ij} = \begin{cases} 0, & \text{At least one of the two cities has a regional GDP not higher than the mean} \\ 1, & \text{Both cities have a regional GDP higher than the mean} \end{cases} \tag{6}$$

The economic proximity matrix E is defined as:

$$E = \begin{bmatrix} e_{11}(t) & \dots & e_{1m}(t) \\ \vdots & \ddots & \vdots \\ e_{m1}(t) & \dots & e_{mm}(t) \end{bmatrix} \tag{7}$$

(4) Organizational proximity

Provincial co-membership serves as the operational measure of organizational proximity, following Yang (2025). Cities within the same province share administrative frameworks, policy environments, and resource-allocation systems that reduce coordination costs; cities across provincial boundaries do not. Accordingly:

$$O_{ij} = \begin{cases} 1, & \text{if cities } i \text{ and } j \text{ belong to the same province} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

These values populate the $m \times m$ organizational proximity matrix O :

$$O = \begin{bmatrix} o_{11}(t) & \dots & o_{1m}(t) \\ \vdots & \ddots & \vdots \\ o_{m1}(t) & \dots & o_{mm}(t) \end{bmatrix} \tag{9}$$

(5) Technological Proximity

Technological proximity is measured using annual patent application volumes, following Yang *et al.* (2025). For each year t , the proximity between cities i and j is:

$$Tech_{ij} = 1 - \frac{|pat_i - pat_j|}{\max |pat_i - pat_j|} \tag{10}$$

where pat_i and pat_j are the patent application totals for cities i and j in year t , and the denominator normalizes by the largest city-pair difference observed that year. Higher values indicate more similar technological scales and closer proximity. The $m \times m$ matrix is:

$$TECH = \begin{bmatrix} tech_{11}(t) & \dots & tech_{1m}(t) \\ \vdots & \ddots & \vdots \\ tech_{m1}(t) & \dots & tech_{mm}(t) \end{bmatrix} \tag{11}$$

6.2. QAP results

6.2.1. QAP correlation analysis

Table 12 reports QAP correlation coefficients for 2019–2023. All estimates are significant at $p < 0.01$, lending strong statistical support to the findings.

Table 12
QAP correlation analysis results.

Time	Variable	Correlation Coefficient	P-value	Standard Deviation	Minimum	Maximum	P≥0	P≤0	Number of Permutations
	geographical proximity	0.202	0.000***	0.062	-0.218	0.184	0.000	1.000	5000
	institutional Proximity	-0.326	0.000***	0.073	-0.268	0.157	1.000	0.000	5000

Table 12. (continued)

Time	Variable	Correlation Coefficient	P-value	Standard Deviation	Minimum	Maximum	P≥0	P≤0	Number of Permutations
2019	economic proximity	0.210	0.004***	0.063	-0.093	0.265	0.004	0.999	5000
	organisational proximity	0.157	0.001***	0.045	-0.148	0.157	0.001	1.000	5000
	technological proximity	-0.256	0.001***	0.072	-0.277	0.164	0.999	0.001	5000
	geographical proximity	0.179	0.000***	0.062	-0.211	0.176	0.000	1.000	5000
	institutional Proximity	-0.350	0.000***	0.081	-0.316	0.154	1.000	0.000	5000
2020	economic proximity	0.291	0.001***	0.067	-0.100	0.291	0.001	1.000	5000
	organisational proximity	0.164	0.000***	0.044	-0.144	0.164	0.000	1.000	5000
	technological proximity	-0.254	0.004***	0.079	-0.311	0.169	0.996	0.004	5000
	geographical proximity	0.227	0.000***	0.067	-0.266	0.196	0.000	1.000	5000
	institutional Proximity	-0.456	0.000***	0.092	-0.456	0.149	1.000	0.000	5000
2021	economic proximity	0.378	0.000***	0.073	-0.123	0.326	0.000	1.000	5000
	organisational proximity	0.132	0.001***	0.039	-0.141	0.143	0.001	1.000	5000
	technological proximity	-0.385	0.000***	0.091	-0.401	0.175	1.000	0.000	5000
	geographical proximity	0.290	0.000***	0.061	-0.203	0.222	0.000	1.000	5000
	institutional Proximity	-0.375	0.000***	0.081	-0.320	0.178	1.000	0.000	5000
2022	economic proximity	0.328	0.000***	0.064	-0.130	0.265	0.000	1.000	5000
	organisational proximity	0.272	0.000***	0.038	-0.117	0.165	0.000	1.000	5000
	technological proximity	-0.269	0.002***	0.079	-0.335	0.182	0.998	0.002	5000
	geographical proximity	0.233	0.000***	0.060	-0.212	0.198	0.000	1.000	5000
	institutional Proximity	-0.391	0.000***	0.084	-0.331	0.189	1.000	0.000	5000
2023	economic proximity	0.375	0.000***	0.065	-0.124	0.317	0.000	1.000	5000
	organisational proximity	0.212	0.000***	0.036	-0.141	0.134	0.000	1.000	5000
	technological proximity	-0.280	0.003***	0.083	-0.390	0.188	0.998	0.003	5000

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

Geographical proximity exhibited a sustained and significant positive correlation with urban collaboration networks over the five years, with coefficients ranging from 0.179 to 0.290. This relatively stable value indicates that geographical proximity serves as a foundational factor driving urban collaboration networks. Institutional proximity, however, demonstrated a stable negative correlation with urban collaboration networks over the five years, with coefficients ranging from -0.456 to -0.326, which implies that cities at the same administrative level are less inclined to collaborate, whereas collaboration is more common between cities at different levels. Economic proximity exhibited a stable positive correlation with urban collaboration networks over the five years, with coefficients rising from 0.210 to 0.378, indicating a marked strengthening trend, suggesting that similar levels of economic development, particularly “strong-strong alliances”, constitute a core factor in fostering collaboration. Organizational proximity also exhibited a stable positive correlation with urban collaboration networks over the five years, with coefficients ranging from 0.132 to 0.272. These relatively stable values indicate that organizational proximity is another significant factor in fostering inter-city collaboration. Technological proximity exhibited a stable negative correlation with urban collaboration networks over the five years, with coefficients ranging from -0.254 to -0.385, which indicates that cities do not tend to cooperate with those possessing similar technological structures, but rather favor collaboration with cities offering strong technological complementarity.

6.2.2. QAP regression analysis

Table 13 presents QAP regression results for 2019–2023. Overall, the model’s explanatory power improved after 2019, with R^2 rising from 0.171 in 2019 to above 0.30 during 2021–2023. Proximity factors thus grew progressively more influential in shaping intercity collaboration.

Table 13

QAP multiple regression analysis results.

Time	Variable	Unstandardized Coefficient	Standardized Coefficient	P-value	R^2	Adj- R^2
2019	geographical proximity	0.124636	0.092881	0.016**	0.171	0.168
	institutional Proximity	-0.136872	-0.219075	0.000***		
	economic proximity	0.110265	0.123566	0.008***		
	organisational proximity	0.080937	0.139556	0.002***		
	technological proximity	-0.136518	-0.130709	0.010***		
2020	geographical proximity	0.055494	0.038558	0.208	0.208	0.204
	institutional Proximity	-0.170519	-0.248230	0.000***		
	economic proximity	0.206799	0.206799	0.000***		
	organisational proximity	0.103002	0.163765	0.001***		

Table 13. (continued)

Time	Variable	Unstandardized Coefficient	Standardized Coefficient	P-value	R ²	Adj-R ²
2021	technological proximity	-0.116462	-0.105491	0.033**	0.350	0.347
	geographical proximity	0.234235	0.136026	0.000***		
	institutional Proximity	-0.205846	-0.249088	0.000***		
	economic proximity	0.328025	0.283058	0.000***		
	organisational proximity	0.084433	0.114995	0.002***		
	technological proximity	-0.299275	-0.215330	0.001***		
2022	geographical proximity	0.248848	0.135686	0.000***	0.304	0.302
	institutional Proximity	-0.220542	-0.249058	0.000***		
	economic proximity	0.306220	0.242607	0.000***		
	organisational proximity	0.182095	0.233852	0.000***		
	technological proximity	-0.150576	-0.103919	0.022**		
	geographical proximity	0.183599	0.100529	0.010***		
2023	institutional Proximity	-0.227912	-0.249665	0.000***	0.304	0.302
	economic proximity	0.392737	0.292483	0.000***		
	organisational proximity	0.149114	0.189528	0.000***		
	technological proximity	-0.175548	-0.117583	0.031**		

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

Geographical proximity generally has a positive effect on collaboration networks. Except for 2020, its coefficient is positive and statistically significant, indicating that nearby cities are more likely to collaborate. Although this effect weakened temporarily in 2020, it recovered in later years, indicating that geographical proximity continues to play an important role in reducing transaction costs and facilitating tacit knowledge transfer (Marek *et al.*, 2017). For new R&D institutions, frequent interaction, trust-building, and the low-cost flow of innovation remain closely related to spatial proximity (Chiswick and Miller, 1999).

Institutional proximity shows a consistently significant negative effect, which suggests that cities at the same administrative level are not necessarily more likely to collaborate. Instead, collaboration may be more likely between cities with different institutional positions and resource endowments. Excessive

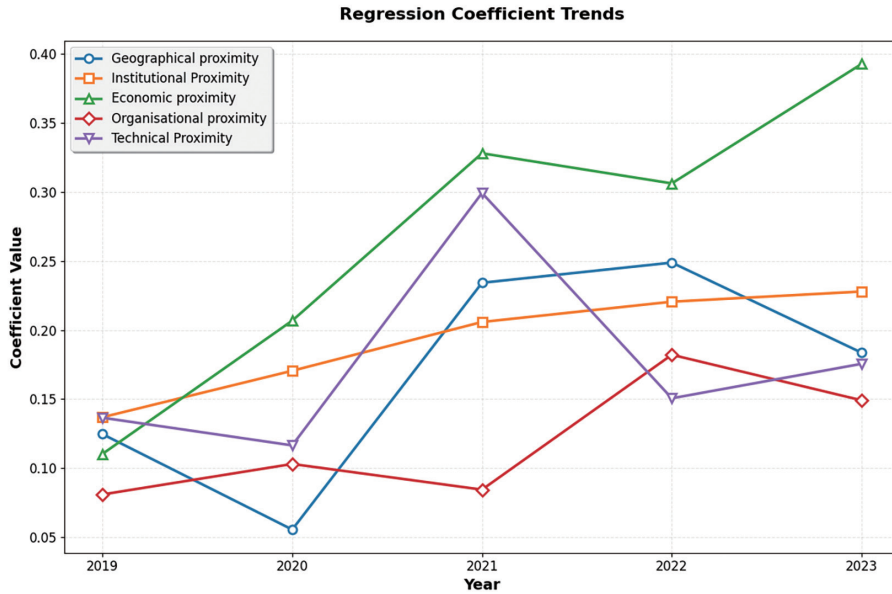


Fig. 8. Trends of QAP regression coefficients (2019-2023).

Note: The figure displays the absolute values of the coefficients to measure their absolute influence.

institutional similarity may limit the entry of new partners and reduce the diversity of collaborations (Xavier Molina-Morales *et al.*, 2015). In the Yangtze River Delta, cross-level collaboration appears to be supported by vertical division of labor, functional complementarity, and administrative coordination (Zhou, 2025).

Economic proximity has a stable and significant positive effect. Cities with similar and relatively strong economic foundations are more likely to build collaborative ties. This may be because they have comparable R&D capacity, talent resources, innovation infrastructure, and industrial demands, which lowers matching costs and supports knowledge diffusion (Chen *et al.*, 2018). Similar demand structures may also encourage intercity collaboration among new R&D institutions. The rising coefficient indicates that “strong-strong” collaboration among economically advanced cities has become more prominent.

Organizational proximity also has a significant positive effect. Cities within the same province are more likely to collaborate because they share similar administrative systems, policy environments, and communication channels. Such proximity helps build institutional trust and social connections (Wang *et al.*, 2021), reduce uncertainty and transaction costs, and improve coordination efficiency (Knoben and Oerlemans, 2006; Jespersen *et al.*, 2018). It also supports smoother knowledge diffusion within provincial boundaries (LeSage *et al.*, 2007) and faster knowledge transfer between organizationally proximate actors (Singh, 2005).

Technological proximity has a significant negative effect throughout the period, which means that cities with similar technological structures are less likely to collaborate, while cities with different technological strengths are more attractive partners. This result points to a technological complementarity effect. Since technological proximity affects knowledge spillovers (Mueller and Zaby, 2019), excessive similarity may lead to knowledge redundancy, reduce learning space, and weaken novelty generation (Nooteboom *et al.*, 2006). It may also reinforce path dependence or technological lock-in (Fernandez *et al.*, 2016). Therefore, new R&D institutions are more likely to support collaboration where heterogeneous

knowledge and complementary capabilities can generate greater innovation value.

6.2.3. Robustness test

QAP is inherently self-validating: its permutation procedure repeatedly reconstructs the null distribution, guarding against spurious correlations arising from network autocorrelation. Two additional robustness checks were conducted. First, the number of random permutations is varied: the default of 2,000 is increased to 2,500, 3,000, and 4,000, respectively, and the results remain consistent with the original findings. Second, the measurement of core variables is replaced; drawing on existing studies, alternative measurement methods for variables such as economic proximity are adopted, and the relational matrices are reconstructed, with the test results again remaining consistent with the original findings. These tests demonstrate that the results of this study are robust.

7. Conclusions and Discussion

7.1. Conclusions

Drawing on patent collaboration data spanning the period from 2011 to 2024, this study examines the spatio-temporal evolution of the intercity network formed by new R&D institutions in the Yangtze River Delta and probes into how multidimensional proximity shaped that evolution. Four main conclusions follow.

First, the collaboration network has continued to expand and shows typical small-world characteristics. The number of intercity collaborative patents increased steadily, while the network scale and connection intensity both strengthened. The rising average degree, high clustering coefficient, and shorter average path length indicate that the network has become more cohesive and efficient. Spatially, it evolved from a “point-axis” structure to a “corridor-based” pattern and then toward a more networked configuration. However, the network still shows shallow connectivity, suggesting that wider collaboration has not yet been matched by deeper integration.

Second, the network has shifted toward a multi-centered structure, with clear differences in city functions. In the early stage, cities such as Changzhou and Nanjing acted as initial collaboration hubs, while Hangzhou and Shanghai played stronger intermediary roles. In the second stage, the network became more concentrated around higher-tier cities, especially Nanjing and Shanghai, with Hangzhou and Hefei emerging as secondary hubs. In the third stage, Hangzhou, Nanjing, Hefei, and Shanghai jointly formed a multi-centered network. At the same time, cities such as Suzhou and Ningbo moved closer to the core, while many others remained peripheral, revealing a persistent regional imbalance.

Third, the network shows a stable core-periphery structure and several cohesive subgroups. The number of core cities first increased and then declined as the threshold for entering the core rose. In the later stage, only cities with the strongest and most frequent ties remained central, while most new cities entered the network from the periphery. Subgroup analysis shows that early collaboration was mainly shaped by geographical proximity, while later stages saw stronger internal cohesion and more inter-subgroup connections, which reflects the gradual deepening of regional integration.

Fourth, multidimensional proximity has differentiated effects on network evolution. Geographical, economic, and organizational proximity have stable positive effects on intercity collaboration, while institutional and technological proximity show negative effects. Except for the fluctuating effect of

technological proximity, the influence of most proximity factors increased over time, indicating that proximity mechanisms have become more important in shaping the collaboration network.

7.2. Discussion

7.2.1. Theoretical implications

This study advances the innovation network theory in three aspects. First, it broadens the scope of network actors. Existing research mainly focuses on firms, universities, and public research institutes (Basso *et al.*, 2021), while paying little attention to new R&D institutions. The results indicate that such institutions function as intermediary organizations (Etzkowitz, 2003). They foster small-world properties in collaboration networks (Valverde *et al.*, 2002) and lowers barriers to cross-agent collaboration.

Second, this study enriches research on innovation networks at the urban scale. The prior studies have been conducted at the macro-regional or micro-actor level (Krätke, 2010; Kauffeld-Monz and Fritsch, 2013). This paper explores the evolution of city-level collaboration networks and bridges the gap between macro and micro research perspectives. It also mitigates the fragmentation of work division within innovation systems (Sun and Bi, 2021).

Third, existing literature generally holds that proximity facilitates collaboration (Mueller and Zaby, 2019), whereas this research identifies a more intricate mechanism. Consistent with previous findings on how spatial and administrative boundaries shape knowledge spillovers (Chiswick and Miller, 1999; LeSage *et al.*, 2007), geographic and organizational proximity exert positive effects on cooperation. By contrast, institutional and technological proximity generate negative impacts. This indicates that collaboration is driven not merely by homogeneity, but also by complementarity and asymmetry among participants (Zhou, 2025).

7.2.2. Practical implications

The findings offer valuable implications for regional integration. Network evolution shows that new R&D institutions have effectively promoted knowledge diffusion and industrial upgrading by building cross-city collaboration corridors. From 2011 to 2024, the gap in total patent output widens from 225 to 8,395, highlighting their critical role in breaking down barriers among industries, universities and research institutes.

In addition, the divergent development of urban functions points to prominent spatial imbalance in the distribution of innovation resources. Leading innovation hubs including Shanghai and Nanjing keep exerting radiating effects. Meanwhile, peripheral cities have increased to 35, accounting for 87.5% of all cities in the region, which reveals growing regional disparities. Targeted policy support is therefore required to strengthen links between peripheral cities and the core network, so as to prevent the Matthew effect in the allocation of innovation resources from worsening.

7.2.3. Policy Implications

First, it is necessary to amplify the radiation capacity of core cities and optimize the multi-center network system. H-H core cities shall lead the development of cross-regional industry-university-research alliances and share innovation resources with peripheral areas. H-L cities can build professional industrial technology alliances to boost collaborative capabilities. L-H cities ought to give full play to their intermediary role through regional technology service platforms. L-L peripheral cities should develop

differentiated industrial clusters and identify complementary entry points for cooperation with core cities.

Second, policies should better coordinate different types of proximity. Since geographic, economic, and organizational proximity promote collaboration, infrastructure integration, provincial coordination, innovation voucher sharing, data sharing, and joint R&D funds should be further strengthened. Since technological and institutional proximity have negative effects, policy should encourage differentiated technological positioning, complementary cooperation between cities, provincial–municipal joint funds, and enclave-economy mechanisms.

Third, growth poles should be cultivated in peripheral cities. The core–periphery analysis shows that strong ties are increasingly concentrated in a small number of core cities, while many peripheral cities remain weakly connected. Policies should help cohesive subgroups move from local clustering toward more open inter-group collaboration. For long-term peripheral cities, a “one city, one policy” approach should be adopted to address their specific weaknesses and avoid uniform policy design.

7.2.4. Limitations and future research

This study has several limitations. First, patent data capture formal collaboration but may overlook informal knowledge exchange, thereby underestimating the network’s actual scope. Second, the sample only includes 882 new R&D institutions in the Yangtze River Delta. Hence, the findings cannot be directly generalized to other urban agglomerations. Third, although the empirical results reveal correlations between proximity factors and network structure, the underlying causal mechanisms remain underexplored. Fourth, the QAP analysis adopts the period of 2019–2023, while the network evolution analysis spans 2011–2024. This discrepancy mainly stems from sparse network data in the early years, which would render QAP regression unreliable prior to 2019. Even so, the relatively short time window for empirical analysis may impair the study’s internal consistency.

Four avenues are proposed for future research. First, non-patent collaboration data can be incorporated to verify the robustness of the network structure. Second, the research scope can be extended to other major urban agglomerations across China for comparative analysis. Third, qualitative approaches can be adopted to further interpret collaboration decision-making and the formation of macro-level networks. Fourth, longer time-series data should be collected to conduct a more comprehensive investigation into the driving mechanisms of collaboration network evolution.

Acknowledgments

This work is supported by the Chinese Academy of Sciences Mission/Other Academy Missions/Special Program for Strategic Planning and Decision Support (E5X04016).

Conflicts of interest

The authors declare no conflict of interest.

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