

Article

Network Dynamics and Key Transmission Pathways of a Provincial Innovation System: A County-Level Analysis of Jiangsu Province, China

Jia Shao and Xingping Wang * 

School of Architecture, Southeast University, Nanjing 210096, China; 220240067@seu.edu.cn

* Correspondence: wxpsx@seu.edu.cn

Abstract

Provincial innovation systems can be understood as complex adaptive networks in which connectivity and resilience-enabling conditions emerge from heterogeneous local capabilities, spatial constraints, and relational configurations. Taking 95 county-level units in Jiangsu Province, China, as the study area, this study constructs a county-level innovation capability index for 2020–2023 across four dimensions: innovation input, innovation output, innovation environment, and innovation performance. Using this index as the mass variable, a gravity-based potential innovation linkage network is developed, and network analysis indicators are applied to examine its stage-specific structural changes, functional differentiation, and key transmission pathways within the model-derived network. The results show that county-level innovation capability increased across the four observations, while the intra-provincial south–north gradient remained evident. The potential network became increasingly connected, but this increase in connectivity did not lead to structural equalization. Instead, linkages were selectively reinforced around high-capability nodes and spatially proximate areas, indicating local clustering, potentially path-dependent organization, and selective connectivity. County-level units performed differentiated systemic roles as core-organizing, system-supporting, and connector nodes, shaped jointly by innovation capability, spatial location, and network embeddedness. The identified key transmission pathways exhibited a multi-level structural configuration involving intra-cluster reinforcement, intercity corridor continuity along the Yangtze River, and short-chain embedding of peripheral nodes. These findings suggest that provincial innovation systems may exhibit selective structural organization rather than uniform relational development, shaped by capability asymmetry, spatial proximity, and relational configuration. Because the network is derived from innovation capability and geographical distance, the identified linkages and pathways represent model-estimated relational opportunities rather than directly observed knowledge, technology, or innovation flows. Within this interpretive boundary, county-level nodes and key transmission pathways provide insights into system connectivity and resilience-oriented governance.



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1. Introduction

Digitalization, regional integration, and the growing mobility of knowledge and production factors have increasingly organized innovation through cross-regional and

multi-actor networks. Systemic disruptions such as the COVID-19 pandemic have further underscored the importance of maintaining connectivity and coordination across heterogeneous actors and places [1]. Provincial innovation systems can therefore be conceptualized as complex adaptive systems in which territorial units with unequal capabilities interact through spatially constrained, multi-scalar, and potentially path-dependent relationships [2]. Within such systems, the innovation capability of a local unit does not automatically translate into system-level influence; rather, its role depends on its position within the broader relational structure. Provincial innovation performance thus emerges from the interaction of node heterogeneity, relational configuration, and network pathways rather than from the simple aggregation of local capabilities [3].

In this study, network-based resilience potential refers to the structural conditions that may enable an innovation network to maintain or reconfigure connectivity and inter-regional accessibility under disruption. These conditions include relational redundancy, alternative linkage routes, bridging positions, and continuity of key transmission pathways. This concept differs from hazard-based resilience approaches that explicitly model performance loss, system availability, recovery trajectories, and restoration under recurrent disruptions [4,5]. The present study therefore does not measure realized resilience to COVID-19 or any other specific shock, but identifies structural characteristics that may support adaptation and network reorganization.

Network analysis provides a systems-oriented approach to examining regional innovation as an emergent outcome of interactions among heterogeneous nodes. Regional innovation performance depends not only on individual node attributes but also on relational configurations and the system-level properties generated through these interactions [6]. Indicators of connectivity, efficiency, clustering, centrality, embeddedness, and robustness can reveal network organization, the distribution of potential transmission capacity, and the nodes or pathways critical to maintaining system connectivity [7]. Existing research follows two complementary strands. Capability-based studies use multidimensional indicators to examine spatial differentiation and spillover effects, showing that local innovation is shaped by both internal resources and broader spatial and institutional contexts [8,9]. Relation-based studies construct networks from patent collaboration, scientific cooperation, technology transactions, or interfirm linkages to identify central, cohesive, and bridging positions [10,11]. Together, these strands demonstrate that regional innovation outcomes emerge from the interaction between localized capabilities and relational embeddedness.

Despite these advances, several gaps remain. First, most existing studies are conducted at the scale of provinces, urban agglomerations, or prefecture-level cities, while intra-provincial innovation structures at the county level remain underexplored. County-level units are not merely finer administrative subdivisions; they are territorial carriers of enterprises, development zones, innovation platforms, industrial capacity, and policy implementation. Analysis at this scale can therefore reveal functional and relational heterogeneity concealed by prefecture-level aggregation.

Second, innovation capability assessment and innovation network analysis are often conducted separately, leaving unclear how differences in local innovation capability are transformed into potential linkages and differentiated network positions under geographical constraints. Stronger innovation capability may increase a unit's relational attractiveness, but does not necessarily determine whether it occupies a core, supporting, or bridging position. Such positions are also conditioned by spatial location, surrounding-node characteristics, and the wider linkage configuration.

Third, existing studies have emphasized aggregate network indicators and node centrality more than the joint organization of key nodes and key transmission pathways [12,13]. Yet provincial connectivity depends not only on highly connected nodes but also on the

routes linking different regional blocks. Joint identification of key nodes and key transmission pathways can therefore reveal how core organization, interregional bridging, and peripheral integration are combined. Because these pathways are derived from modeled relationships, they are interpreted as potential structural channels rather than realized flows of knowledge, technology, or capital.

Jiangsu Province provides a suitable case for examining these issues. It has a high concentration of innovation resources, a strong manufacturing and industrial base, and marked intra-provincial disparities. At the same time, it contains a dense system of county-level units and active cross-boundary economic and innovation linkages, making it an appropriate setting for investigating the structural differentiation and transmission mechanisms of a provincial innovation system [14]. This study takes 95 county-level units in Jiangsu Province as the research objects and constructs a county-level innovation capability evaluation system based on four dimensions: innovation input, innovation output, innovation environment, and innovation performance. On this basis, a potential innovation linkage network is developed by integrating a gravity model with social network analysis. The study further identifies the overall network structure, key nodes, and key transmission pathways of the provincial innovation system.

Specifically, this study addresses three research questions. First, what spatial differentiation patterns does county-level innovation capability exhibit within Jiangsu Province, and what finer-grained characteristics can be revealed at the county scale? Second, how is county-level innovation capability transformed into potential innovation linkages and differentiated network positions under geographical constraints? Third, which nodes and key transmission pathways occupy structurally important positions in maintaining connectivity and linking core, transitional, and peripheral areas?

This study makes three main contributions. First, it extends provincial innovation-system research to the county scale, revealing heterogeneous functional and relational roles that are often concealed by prefecture-level aggregation. Second, it integrates innovation capability assessment with gravity-based potential-linkage modeling and distinguishes node attributes from network positions, demonstrating the additional relational insights provided by network analysis beyond capability-based evaluation. Third, it connects key-node identification with potential backbone pathway analysis to explain how core-organizing, system-supporting, and connector nodes jointly shape provincial innovation connectivity. Overall, the study provides a stage-specific relational explanation of how capability asymmetry, geographical proximity, and network embeddedness shape provincial innovation-system organization and the structural conditions associated with adaptive network capacity.

2. Theoretical Foundations and Analytical Framework

Drawing on the conceptual distinction between node attributes and relational structures, this study develops a theoretical framework comprising “innovation capability–potential linkages–network embeddedness–potential transmission conditions”. The framework explains how the innovation capability of county-level units is translated into potential linkages under spatial constraints, how the configuration of these linkages generates differentiated network positions, and how such positions shape nodes’ structural opportunities and potential transmission conditions.

2.1. Regional Innovation Systems and County-Level Innovation Capability

Regional innovation systems theory views innovation as a systemic process embedded in a region-specific industrial base, knowledge infrastructure, and institutional environment. Innovation performance depends not only on the availability of innovation resources but also on interactions among different actors and territorial units [15,16]. A provincial

innovation system is therefore not merely an aggregation of the innovation capabilities of individual county-level units, but a relational system constituted by heterogeneous territorial nodes and the linkages among them.

Provincial administrative regions are governed through relatively unified science and technology policies, industrial governance arrangements, and mechanisms for allocating innovation resources, while simultaneously encompassing county-level units with markedly different development foundations. These units serve as important territorial carriers of enterprises, innovation infrastructure, industrial resources, and policy implementation. Their innovation capability reflects their overall foundations in innovation inputs, knowledge production, the innovation environment, and the commercialization of innovation outcomes. However, capability alone does not fully reveal their structural roles within the provincial relational system. County-level units with similar levels of innovation capability may perform different functions because of differences in their linkage partners and embedded positions. Research on provincial innovation systems therefore needs to move beyond the assessment of node attributes toward the analysis of relational structures, thereby identifying features of network organization that cannot be captured by innovation capability rankings alone [17,18].

2.2. Spatial Constraints, Potential Linkages, and Network Embeddedness

Proximity theory suggests that interregional innovation interactions are jointly shaped by multiple dimensions of proximity, including geographical, cognitive, organizational, social, and institutional proximity [19]. Geographical proximity can reduce communication and coordination costs, but is not sufficient on its own to determine whether actual innovation collaboration will emerge [20].

Accordingly, this study conceptualizes county-level innovation capability as both the resource basis for potential linkage formation and a source of relational attractiveness, while geographical distance represents resistance to spatial interaction. The gravity model is therefore employed as a parsimonious spatial-interaction framework rather than as a predictive model of realized collaboration. When directly observed relational data are incomplete or unavailable, it provides a structured estimate of the relative opportunities for linkage formation under a capability–attraction–distance–resistance mechanism. In theoretical terms, stronger innovation capability increases a county-level unit’s attractiveness as a potential linkage partner, whereas greater geographical distance raises the costs of communication, coordination, and exchange.

Innovation capability should not, however, be equated with cognitive proximity, and the gravity model does not provide a comprehensive representation of multidimensional proximity. Because this study does not directly measure cognitive, organizational, social, or institutional proximity, and does not employ observed interaction data such as co-patenting, technology transactions, interfirm collaboration, or talent mobility, the resulting network represents model-estimated relational potential generated by capability attraction and distance constraints. It therefore captures potential structural linkages rather than realized flows of knowledge, technology, or innovation resources.

Once potential linkages are represented as a network, innovation capability and network position constitute two interrelated but conceptually distinct dimensions. Network embeddedness theory emphasizes that the role of a node depends not only on the resources it possesses but also on how it is situated within the broader relational structure [21]. Innovation capability is a node attribute, whereas network position is a structural attribute. County-level units with high innovation capability do not necessarily occupy critical bridging positions, while units with moderate capability may attain considerable structural importance by connecting different regional clusters. On this basis, this study compares

innovation capability rankings, network centrality rankings, and key-node rankings to determine whether network analysis provides structural information beyond that captured by capability assessment.

2.3. Network Position, Structural Opportunities, and Potential Transmission

Network position shapes the conditions under which nodes access information, organize linkages, and connect different groups, thereby generating differentiated structural opportunities. Depending on the metric employed, higher centrality may indicate a broader range of linkages, a more prominent intermediary position, or greater network-wide accessibility, thereby improving a node's structural access to potential collaboration partners. Embeddedness within densely connected local clusters can facilitate repeated interactions and stable collaboration, but may also produce information redundancy and regional lock-in. Nodes positioned between different clusters may span structural holes and connect groups that otherwise lack direct linkages, thereby gaining access to non-redundant information and brokerage opportunities [22,23].

Research on innovation diffusion further indicates that innovation does not spread uniformly across space, but is shaped by communication channels, node accessibility, and relational structures [24]. Nevertheless, the presence of accessible paths within a network does not imply that innovation has actually diffused along those paths. In the potential network constructed in this study, centrality, local embeddedness, and bridging positions represent structural conditions for organizing linkages, sustaining regional interactions, and connecting different regional clusters, rather than realized innovation transmission outcomes.

There is therefore no direct linear correspondence between innovation capability and potential transmission conditions. County-level innovation capability provides the node-level basis for potential linkage formation, while geographical distance imposes spatial constraints. The configuration of these linkages shapes network embeddedness, which in turn creates differentiated structural opportunities by influencing accessibility, relational coordination, and cross-group connectivity. As schematically summarized in Figure 1, this analytical logic links node attributes, potential relational structures, network positions, and potential transmission conditions. Accordingly, the identification of key nodes and key transmission pathways is intended to reveal structurally important positions and potential channels within the model-derived network, rather than observed innovation flows.

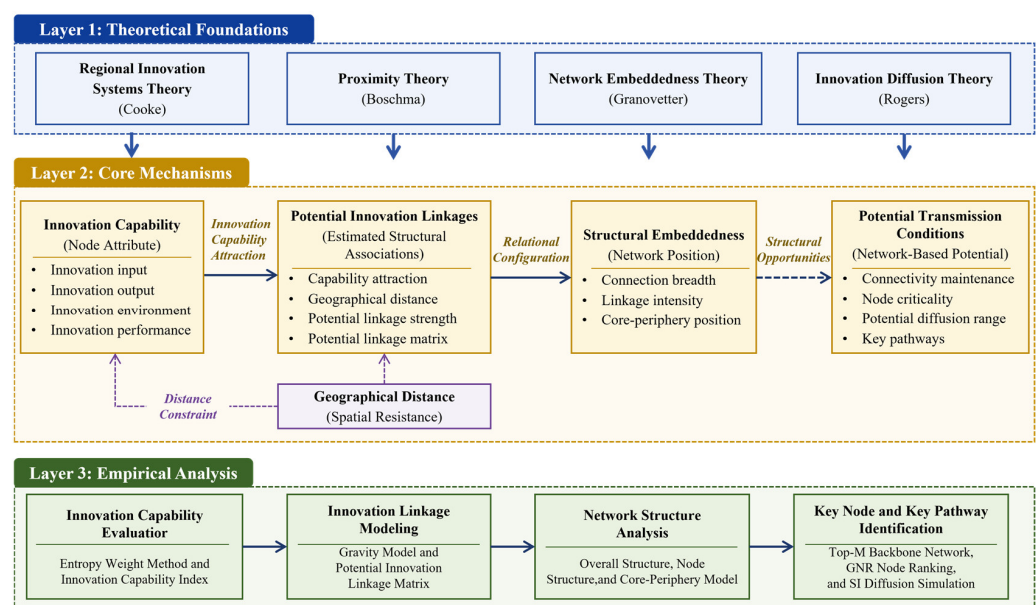


Figure 1. A county-level analytical framework for provincial innovation systems.

3. Materials and Methods

3.1. Study Area and Data Sources

This study uses 95 county-level units in Jiangsu Province, including county-level cities and municipal districts, as the units of analysis, covering the period from 2020 to 2023. This period was selected to ensure consistency in indicator definitions, administrative boundaries, and data availability across all county-level units. Given the relatively short observation window, the analysis focuses on stage-specific structural changes during 2020–2023 rather than long-term innovation trends or interregional convergence. The spatial distribution of the study area is shown in Figure 2. To further reveal the regional differentiation of the provincial innovation network, the study area is divided into three major regions—Southern Jiangsu, Central Jiangsu, and Northern Jiangsu—based on the commonly used regional classification of Jiangsu Province. Specifically, Southern Jiangsu includes Nanjing, Suzhou, Wuxi, Changzhou, and Zhenjiang; Central Jiangsu includes Nantong, Yangzhou, and Taizhou; and Northern Jiangsu includes Xuzhou, Lianyungang, Huai'an, Yancheng, and Suqian. This classification is widely adopted in existing studies and corresponds well to intra-provincial differences in industrial foundations, innovation resource agglomeration, and regional linkages, thereby providing a consistent spatial reference framework for the subsequent comparative analysis.

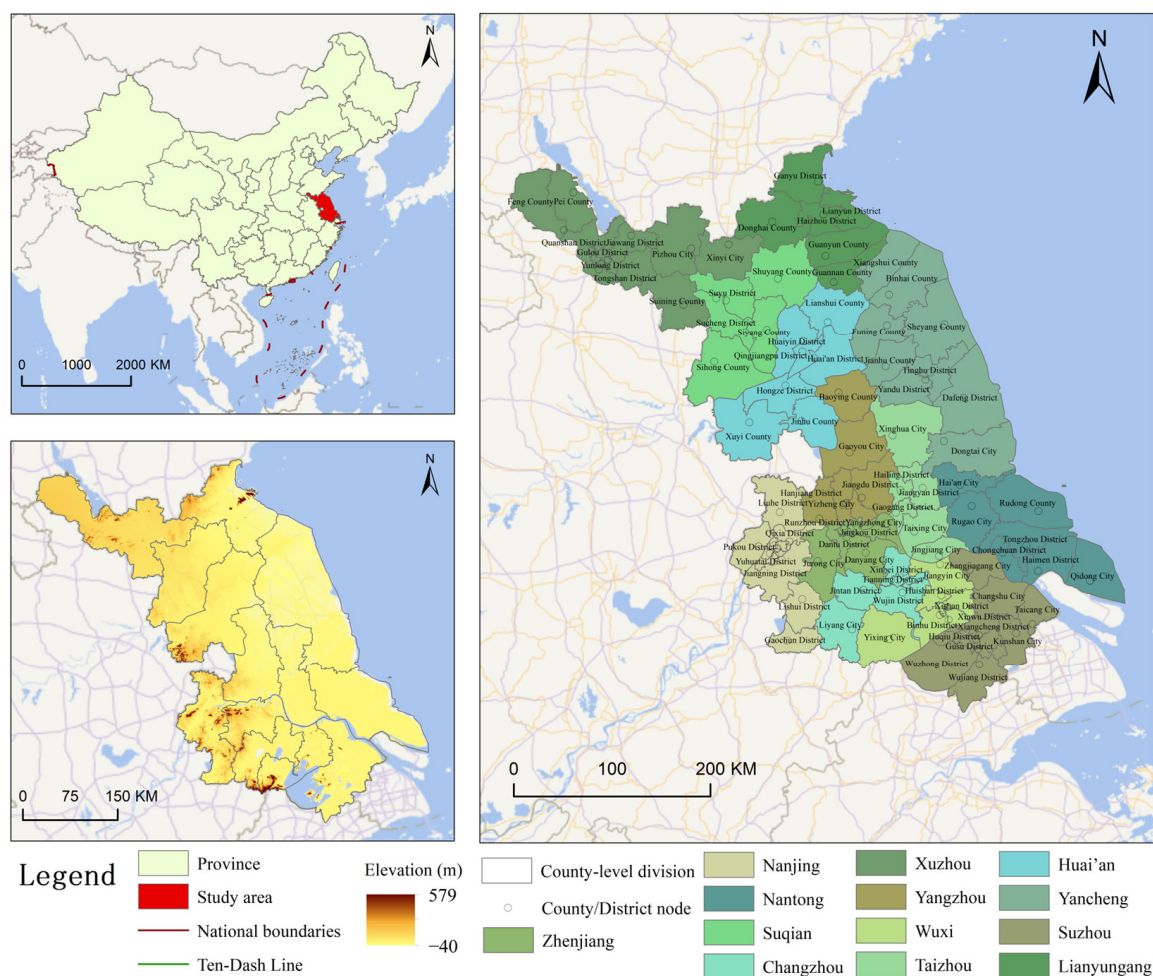


Figure 2. Study area and regional divisions of Jiangsu Province.

The research data were mainly obtained from the statistical yearbooks of cities in Jiangsu Province, county-level statistical yearbooks, and county-level statistical bulletins on national economic and social development from 2020 to 2023. Enterprise-level data were

compiled from the CSMAR database, the Qichacha platform, and relevant publicly available directories. The number of regulations and policy documents supporting innovation was collected from PKULaw, while the annual area of newly supplied industrial land through land conveyance was obtained from the China Land Market website. The remaining indicators were mainly derived from statistical yearbooks and statistical bulletins. For a small number of missing values, linear interpolation was applied to ensure the continuity and comparability of the panel data.

3.2. Methods

To systematically characterize differences in innovation capability across county-level units and their spatial association patterns, this study develops an analytical framework of “innovation capability evaluation–innovation linkage modeling–network structure analysis–key pathway identification.” With innovation capability as the analytical foundation, this framework depicts regional relational structures through potential innovation linkages and further reveals the spatial organization and structural connectivity of potential innovation linkages. The computational analyses were conducted using Python (v3.13.6).

3.2.1. County-Level Innovation Capability Indicator System

Existing studies suggest that regional innovation capability is commonly evaluated using either single indicators or comprehensive indicator systems. Comprehensive evaluation methods have been widely adopted because they can capture the multidimensional nature of innovation activities [25]. From a systems perspective, county-level innovation capability can be regarded as a composite node attribute generated by the interaction of factor input, knowledge output, environmental support, and performance conversion. It reflects not only the agglomeration of innovation resources, such as R&D funding, innovation talent, and technological platforms, but also the capacity of local innovation systems to support knowledge generation, industrial application, and sustained diffusion [26]. In the context of high-quality development, incorporating resource and environmental constraints also helps avoid equating innovation capability with scale expansion alone [27].

Based on data availability and representativeness at the county level, this study constructs an innovation capability evaluation system covering four dimensions: innovation input, innovation output, innovation environment, and innovation performance. A total of 14 indicators are selected, as shown in Table 1 [28–30]. Innovation input reflects the allocation of R&D funding, innovation talent, and technological platforms; innovation output reflects knowledge creation and technological achievements; innovation environment captures external support conditions, including the enterprise base, policy support, industrial ecosystem, and platform-based spatial conditions; and innovation performance measures industrial transformation and resource-efficient development. It should be noted that the innovation environment dimension includes the annual area of newly supplied industrial land through land conveyance and the number of national- and provincial-level development zones. These two indicators do not directly measure innovation output. Rather, they characterize the spatial capacity for accommodating innovation-related industrial activities and the institutional platform foundation supporting innovation resource organization and transformation. Overall, the innovation capability index serves both as a multidimensional measurement of county-level innovation development and as a node attribute for constructing the potential innovation linkage network, thereby linking local capability differences with subsequent network structure analysis.

Table 1. Indicator system for evaluating county-level innovation capability.

Primary Dimension	Secondary Indicator	Indicator Type	Description
Innovation input	R&D expenditure intensity	Positive	Measures the level of regional investment in research and development
	Number of provincial-level enterprise technology centers	Positive	Reflects the scale of enterprise innovation platforms and technological carriers
	Number of higher education institutions	Positive	Represents the foundation of regional research institutions and talent resources
	Number of R&D personnel in listed companies	Positive	Reflects enterprise R&D input and technological innovation capability
Innovation output	Number of patents granted	Positive	Measures the quantity of technological achievements
	Number of invention patents per 10,000 people	Positive	Reflects the per capita output of innovation achievements
Innovation environment	Number of high-tech enterprises	Positive	Reflects the scale of industrial innovation actors in county-level units
	Number of specialized and sophisticated “Little Giant” enterprises	Positive	Captures the specialized innovation capability of small and medium-sized enterprises
	Number of newly established digital economy enterprises	Positive	Reflects the vitality of the innovation ecosystem
	Annual area of newly supplied industrial land through land conveyance	Positive	Reflects the capability to supply industrial space and the spatial foundation for accommodating innovation-oriented industries
	Number of national- and provincial-level development zones	Positive	Reflects the foundation of regional industrial platforms, park-based carriers, and institutionalized development spaces
	Number of innovation policy documents	Positive	Measures the strength of policy support for innovation
	Share of high-tech industrial output value in the total output value of above-designated-size industries	Positive	Reflects the driving role of scientific and technological innovation in industrial development
Innovation performance	Total energy consumption	Negative	Measures the pressure of resource consumption associated with innovation-driven development

Data were standardized using min–max normalization to transform indicators with different units into values within the interval [0, 1]. For positive indicators:

$$Z_{ij} = \frac{X_{ij} - X_j^{\min}}{X_j^{\max} - X_j^{\min}} \quad (1)$$

For negative indicators:

$$Z_{ij} = \frac{X_j^{\max} - X_{ij}}{X_j^{\max} - X_j^{\min}} \quad (2)$$

where X_{ij} and Z_{ij} denote the original and normalized values of indicator j for county-level unit i , respectively, and $X_j^{\max}$ and $X_j^{\min}$ are the corresponding maximum and minimum values.

The normalized proportion, entropy value, and information utility were calculated as follows:

$$P_{ij} = \frac{Z_{ij}}{\sum_{k=1}^n Z_{kj}} \quad (3)$$

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^n P_{ij} \ln P_{ij} \quad (4)$$

$$D_j = 1 - E_j \quad (5)$$

where n is the number of county-level units and $P_{ij} \ln P_{ij} = 0$ when $P_{ij} = 0$. The weight of indicator j was then calculated as:

$$W_j = \frac{D_j}{\sum_{k=1}^m D_k} \quad (6)$$

where m is the number of indicators. The innovation capability index was finally obtained as:

$$I_i = \sum_{j=1}^m W_j Z_{ij} \quad (7)$$

where I_i represents the innovation capability index of county-level unit i . A higher value indicates a higher level of innovation capability. The resulting index was used as a node attribute in constructing the provincial potential innovation linkage network.

3.2.2. Measurement of Potential Innovation Linkages

The gravity model, originally derived from Newtonian gravitation, has been widely adapted in regional economics and spatial-interaction research to estimate interregional linkage potential [31,32]. Its theoretical premise is that interaction potential increases with node capacity and decreases with spatial friction. Given that innovation activities exhibit spatial spillover effects and distance-decay characteristics, this study uses the county-level innovation capability index to represent relational attractiveness and employs inter-county geographical distance to capture spatial resistance. The model therefore estimates the relative propensity for potential linkage formation under a capability–distance framework. The model for measuring the strength of potential innovation linkages between county-level units is specified as follows [33]:

$$G_{ij} = \frac{I_i \times I_j}{D_{ij}} \quad (8)$$

where G_{ij} represents the strength of potential innovation linkages between county-level unit i and county-level unit j ; I_i and I_j represent the innovation capability indices of county-level unit i and county-level unit j , respectively; and D_{ij} represents the geographical distance

between the two districts or counties. In this study, “potential innovation linkages” refer to model-estimated structural associations jointly determined by innovation capability and geographical distance, rather than observed interactions such as patent collaboration, technology transactions, or interfirm cooperation. Similar gravity-based approaches have been used to estimate regional and interprovincial innovation linkages when direct interaction data are incomplete or difficult to obtain [34,35]. Accordingly, the resulting network represents potential connectivity and relational opportunities rather than realized innovation flows.

The model assumes that stronger innovation capability increases relational attractiveness, whereas geographical distance imposes a monotonic constraint on interaction. It does not explicitly capture cognitive, organizational, institutional, or industrial proximity, pre-existing collaboration, or directional flows. Moreover, because innovation capability enters the model directly, some correspondence between capability rankings and network prominence is expected. The subsequent distinctiveness analysis therefore examines whether network-position indicators provide additional structural information beyond capability rankings.

Based on the estimated linkage strengths, annual county-level potential innovation linkage matrices were constructed for the 95 county-level units in Jiangsu Province. For temporal comparability, all unique county-pair linkage strengths from 2020 to 2023 were pooled, and the 80th percentile of the pooled distribution (P80) was adopted as the fixed global binarization threshold. In each annual matrix, linkages equal to or above this threshold were coded as 1 and the remainder as 0, with diagonal elements set to 0. The same absolute threshold was applied across all four years, allowing annual network density to vary while retaining approximately the strongest 20% of linkages in the pooled distribution. Sensitivity was further assessed using the alternative P75 and P85 thresholds.

3.2.3. Structural Analysis of the Potential Innovation Linkage Network

Network analysis provides a set of quantitative tools for characterizing the structural properties of relational matrices. Previous studies have combined modified gravity models with network analysis to examine the structural characteristics of regional innovation networks and spatial correlation networks. In this study, these tools are applied to the gravity-based potential innovation linkage network to examine its connectivity, accessibility, clustering, node embeddedness, and hierarchical organization [36].

Specifically, at the overall level, network density, average degree, global efficiency, and average clustering coefficient are used to measure overall network connectivity, the average scale of node connections, topological accessibility, and local clustering, respectively. At the node level, degree centrality and node strength are used to characterize connection breadth and cumulative linkage intensity, respectively, thereby revealing complementary dimensions of node-level structural prominence within the potential innovation linkage network. At the hierarchical level, the core–periphery model is used to identify core, transitional, and peripheral areas within the network, revealing its hierarchical differentiation pattern [37]. The combined use of multiple indicators helps systematically characterize both the overall and local features of the innovation network. The specific meanings of these indicators are shown in Table 2.

Table 2. Metrics for measuring the structure of the county-level potential innovation linkage network.

Analysis Level	Indicator	Explanation	Research Function
Overall structure	Network density	The ratio of the actual number of linkages in the network to the maximum possible number of linkages.	Measures the overall connectivity and structural compactness of the innovation network.
	Average degree	The average number of direct linkages per node in the network.	Reflects the overall scale of innovation linkages among county-level units, as well as the average level of node connectivity.
	Global efficiency	The average reciprocal shortest-path distance between all node pairs.	Measures network-wide topological accessibility within the potential innovation linkage structure.
	Average clustering coefficient	The average degree to which local closed relationships are formed among neighboring nodes in the network.	Characterizes the local clustering features and block-based organization of the innovation network.
Node structure	Degree centrality	The number of nodes directly connected to a given node.	Reflects the breadth of connections among county-level units within the potential innovation linkage network.
	Node strength	The sum of the weights of the edges connected to a given node.	Reflects the linkage intensity of county-level units within the potential innovation linkage network.
Network structure	Core–periphery model	Identifies core, transitional, and peripheral areas based on the concentration and distribution of linkages among nodes.	Reveals the hierarchical structural characteristics and spatial differentiation pattern of the innovation network.

3.2.4. Key Transmission Pathway Identification

In a model-derived potential network, a limited set of strong linkages and structurally important nodes can summarize the backbone organization of relational opportunities. Accordingly, identifying key transmission pathways helps reveal the principal structural channels connecting county-level units and regional blocks without implying the actual transmission of knowledge, technology, or innovation resources.

First, the original innovation linkage matrix was sparsified. Since the innovation linkage matrix calculated using the gravity model is typically a complete network containing a large number of weak linkages, directly using it for pathway identification may obscure the main linkage structure. To highlight the primary innovation linkages, this study adopts the Top-M sparsification method, which retains only the top M linkages with the largest weights from the connections of each node, while setting the weights of the remaining edges to zero, thereby constructing a sparse innovation network. Compared with the uniform threshold method, the Top-M approach can preserve relatively stable strong-linkage structures among different nodes and reduce the interference of weak linkages in identifying the main transmission structure. It should be noted that the uniform-threshold network was used to compare overall

structural evolution across years, whereas the Top-M backbone network was used to extract dominant linkages and key transmission pathways after filtering weak ties.

On this basis, the GNR node-ranking method was used to identify key nodes in the network [38,39]. This method jointly considers the structural impact of node removal on network connectivity and the direct normalized degree centrality of the node itself, thereby measuring the comprehensive influence of nodes on network connectivity and structural reach. The comprehensive importance of a node is expressed as:

$$S_i = LS_i + DS_i \quad (9)$$

where S_i represents the comprehensive importance score of node i , LS_i indicates the extent of the node's influence on the network's connectivity structure, and DS_i denotes the node's normalized degree centrality. A higher value of S_i indicates that the node is more likely to simultaneously influence both network stability and structural reach. Furthermore, the SI (Susceptible–Infected) simulation was used to estimate the simulated structural reach of each node when it was initialized as the source under standardized simulation conditions, and functional differences were further analyzed by combining the innovation capability index, normalized degree centrality, and simulated structural reach.

Finally, based on the key node identification results and the backbone linkage network, key nodes and their associated edges were extracted to construct a key pathway subnetwork of Jiangsu Province's innovation network, which was used to identify the principal backbone channels of potential innovation linkages. Considering that the Top-M parameter may affect the identification results of key nodes and key pathways, this study conducts a parameter sensitivity analysis using adjacent Top-M schemes in the subsequent robustness test.

4. Results

4.1. Spatiotemporal Patterns of County-Level Innovation Capability

4.1.1. Temporal Variation in County-Level Innovation Capability

From a temporal perspective, the innovation capability of county-level units in Jiangsu Province increased across the four observations from 2020 to 2023. Figure 3 shows that the average innovation capability of county-level units in Southern, Central, and Northern Jiangsu all increased, although the magnitude of improvement varied considerably, while the south-to-north gradient remained evident throughout the observation period.

By region, county-level innovation capability in Southern Jiangsu remained at a high level within the province throughout the study period and recorded the largest increase, with particularly notable growth between 2021 and 2022, indicating that its leading position was maintained during the observation period. County-level innovation capability in Central Jiangsu generally remained at an intermediate level and increased during the study period, although its rate of increase was lower than that of Southern Jiangsu and its year-to-year variation was relatively limited. County-level innovation capability in Northern Jiangsu remained relatively low overall, but its average level also increased across the four observations, indicating some improvement in low-value areas. However, compared with Southern and Central Jiangsu, the overall improvement in Northern Jiangsu remained limited, and the south-to-north ordering remained evident throughout the observation period.

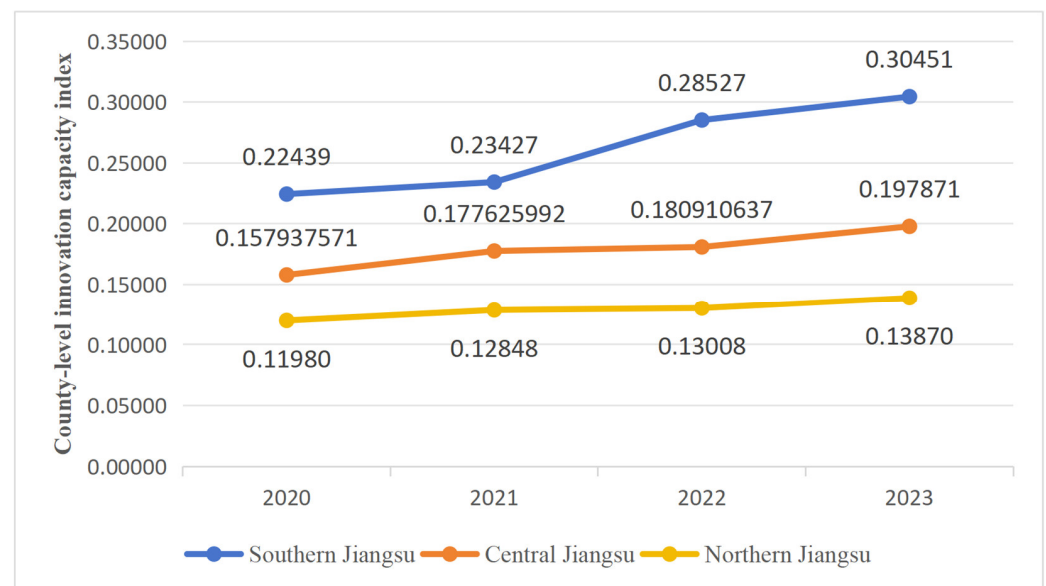


Figure 3. Changes in average county-level innovation capability in Southern, Central, and Northern Jiangsu, 2020–2023.

Overall, the four observations from 2020 to 2023 were characterized by the continued dominance of high-value areas, increases in intermediate areas, and improvements in low-value areas. County-level innovation capability increased overall, while the regional gradient remained evident during the observation period. The observed changes were therefore spatially uneven and occurred largely within the existing gradient structure; they should not be interpreted as evidence of long-term regional convergence.

4.1.2. Spatial Differentiation in County-Level Innovation Capability

From 2020 to 2023, county-level innovation capability in Jiangsu Province exhibited a clear south–north gradient. County-level analysis further revealed more fine-grained differentiation than the conventional division into Southern, Central, and Northern Jiangsu. High-value units were concentrated in several core areas of Southern Jiangsu; selected river-side counties and central urban districts performed relatively strongly in Central Jiangsu; and a small number of central urban districts stood out in Northern Jiangsu (Figure 4).

Southern Jiangsu remained the province’s principal high-value concentration area, although innovation capability was unevenly distributed within the region. Relatively high levels were observed in Xuanwu, Gulou, and Jiangning districts in Nanjing; Huqiu and Wuzhong districts and Kunshan City in Suzhou; Wujin and Xinbei districts in Changzhou; and Xinwu and Binhu districts and Jiangyin City in Wuxi. Together, these units constituted the principal high-value nodes of county-level innovation capability. Central Jiangsu generally exhibited intermediate levels, with localized concentrations in Chongchuan, Tongzhou, and Hanjiang districts, Hai’an City, and Jiangyan District. However, these relatively strong units remained spatially discontinuous, and no contiguous high-value area was observed. Northern Jiangsu was dominated by low- and medium-low-value units but displayed considerable internal variation. Tongshan and Quanshan districts and Suining County in Xuzhou, Qingjiangpu District in Huai’an, and Tinghu District in Yancheng performed relatively well compared with surrounding counties. Improvements in Northern Jiangsu were therefore concentrated in central urban areas and a limited number of relatively advantaged county-level units rather than broadly distributed across the region.

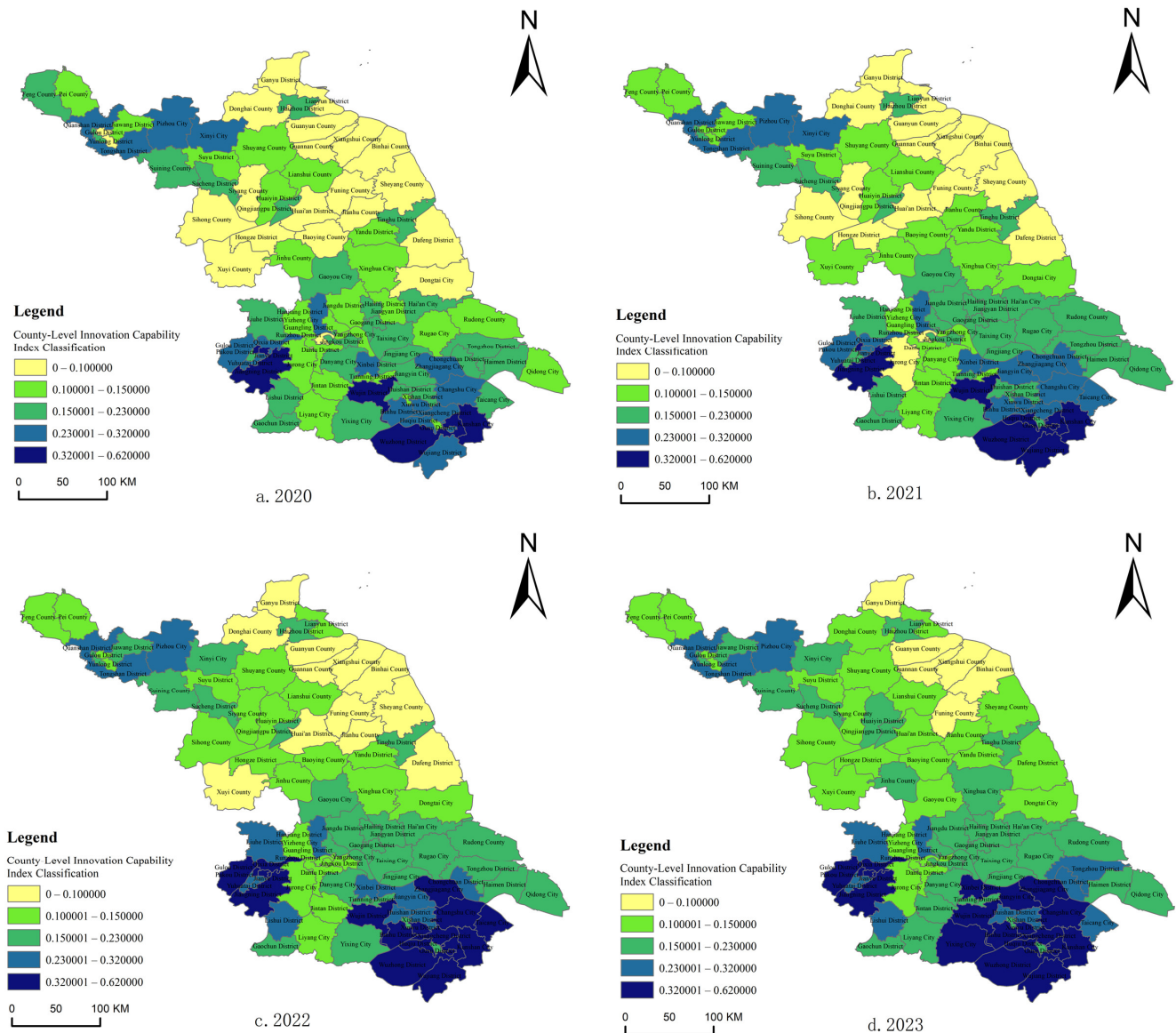


Figure 4. Spatial distribution pattern of county-level innovation capability in Jiangsu Province, 2020–2023.

Across the four observations, the spatial pattern of county-level innovation capability in Jiangsu Province remained generally stable during the study period, while localized hierarchical adjustments gradually emerged. Southern Jiangsu was mainly characterized by the continued strengthening of existing high-value core county-level units; Central Jiangsu by the relative improvement of riverside counties and some central urban areas; and Northern Jiangsu by localized improvement in a small number of county-level units with relatively strong foundations. These changes were spatially uneven and occurred largely within the existing regional gradient. The results therefore indicate a stage-specific pattern characterized by persistent core dominance and localized improvement, rather than evidence of long-term regional convergence. This differentiated spatial configuration provides the node-attribute basis for constructing the potential innovation linkage network.

4.2. Structural Characteristics of the County-Level Potential Innovation Linkage Network

4.2.1. Overall Network Structure and Temporal Variation

Based on the county-level innovation capability index and inter-county geographical distances, this study constructed a potential innovation linkage network for Jiangsu

Province using the gravity model. After binarizing the annual linkage matrices using a fixed global P80 threshold, network density, average degree, global efficiency, and average clustering coefficient were used to characterize changes in overall connectivity, direct linkage extent, topological accessibility, and local clustering during 2020–2023 (Table 3). These indicators capture, respectively, the overall level of network connectivity, the average number of direct linkages per node, network-wide accessibility in topological terms, and the extent of local clustering among neighboring nodes.

Table 3. Overall structural indicators of the county-level innovation network in Jiangsu Province.

Indicator	2020	2021	2022	2023
Network density	0.163	0.180	0.216	0.241
Average degree	15.326	16.926	20.253	22.695
Global efficiency	0.411	0.430	0.460	0.498
Average clustering coefficient	0.678	0.692	0.698	0.715

As shown in Table 3, all four network metrics increased during the observation period. Network density rose from 0.163 in 2020 to 0.241 in 2023, while average degree increased from 15.326 to 22.695. Under the same threshold, these changes indicate that a larger number of potential innovation linkages were retained and that county-level units became more extensively connected within the model-derived network. Global efficiency increased from 0.411 to 0.498, indicating improved network-wide accessibility, while the average clustering coefficient rose from 0.678 to 0.715, reflecting stronger local closure among neighboring nodes. The simultaneous increase in these indicators therefore suggests broader network connectivity accompanied by stronger local clustering, rather than a spatially uniform increase in potential linkages.

The spatial pattern shown in Figure 5 further supports this interpretation. In 2020, potential innovation linkages were mainly concentrated in Nanjing and the Suzhou–Wuxi–Changzhou area, forming several localized high-density clusters in Southern Jiangsu. Central and Northern Jiangsu, by contrast, showed relatively sparse linkages and weaker network embeddedness. By 2023, linkages within Southern Jiangsu had become denser, and the connections between the Nanjing block and the Suzhou–Wuxi–Changzhou block had further strengthened. At the same time, some riverside county-level units in Central Jiangsu became more closely connected with the Southern Jiangsu core, suggesting a gradual improvement in the network embeddedness of transitional areas. Northern Jiangsu also exhibited several localized linkages, but these were mainly scattered connections or short-chain access points, rather than continuous high-density transmission structures.

Overall, the county-level innovation network in Jiangsu Province exhibited higher connectivity, greater topological accessibility, and stronger local clustering in 2023 than in 2020. However, strong potential linkages remained concentrated in Southern Jiangsu, particularly in Nanjing and the Suzhou–Wuxi–Changzhou–Zhenjiang area. Central and Northern Jiangsu were incorporated into the provincial network through an uneven combination of riverside nodes, central urban districts, and localized linkage clusters. The results therefore indicate a hierarchical and block-based network configuration during the observation period, characterized by broader connectivity alongside persistent regional differentiation.

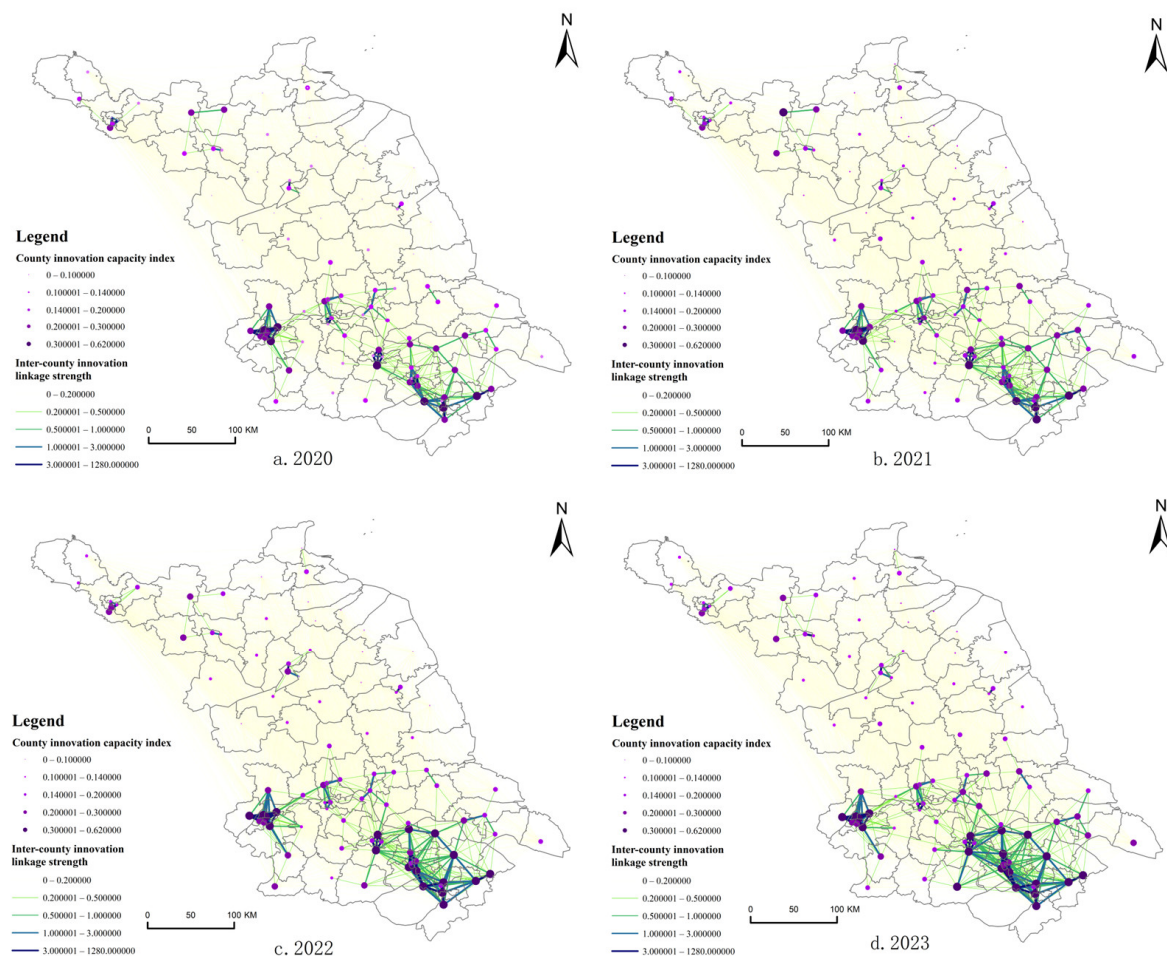


Figure 5. Changes in the county-level potential innovation linkage network in Jiangsu Province, 2020–2023.

4.2.2. Core Nodes and Structural Hierarchy

To identify node-level connectivity and hierarchical differentiation within Jiangsu's county-level potential innovation linkage network, this study combined degree centrality, node strength, and core–periphery analysis. Degree centrality, calculated from the baseline P80-binarized network, captures the breadth of a node's direct connections; node strength, calculated from the original weighted linkage matrix, measures the cumulative intensity of its potential linkages [40]; and core–periphery analysis, applied to the binary network, identifies each node's position within the network hierarchy [41]. Together, these measures characterize county-level units along three complementary dimensions—connection breadth, linkage intensity, and structural embeddedness—while retaining both the topology of the binarized network and the heterogeneity of modeled linkage strengths.

The degree centrality results show that highly connected nodes exhibited consistent prominence and regional concentration across the four observations (Table 4). Wujin District, Xinbei District, Jiangning District, and Jiangyin City ranked among the top nodes for four consecutive years, indicating their strong direct connectivity within the provincial potential innovation linkage network. Among them, Wujin District and Xinbei District consistently occupied the top two positions, reflecting their wide-area connectivity advantages within the high-density linkage area of Southern Jiangsu; Jiangning District and Jiangyin City, respectively, played important connecting roles in the Nanjing block and the Suzhou–Wuxi–Changzhou area. County-level units such as Hanjiang District, Binhu District, Xinwu District, Zhangjiagang City, Huqiu District, Jintan District, Huishan District, and Yixing City entered the top ten in different years, indicating that highly connected

nodes are mainly distributed in county-level units with strong innovation capabilities in Southern Jiangsu and a few connecting nodes in Central Jiangsu, rather than being dominated by a single city.

Table 4. Top ten county-level units by degree centrality in Jiangsu’s potential innovation linkage network.

2020		2021		2022		2023	
County-Level Unit	Value	County-Level Unit	Value	County-Level Unit	Value	County-Level Unit	Value
Wujin District	0.5213	Wujin District	0.5426	Wujin District	0.5638	Wujin District	0.5957
Xinbei District	0.4362	Xinbei District	0.4468	Xinbei District	0.5213	Xinbei District	0.5745
Jiangning District	0.3511	Jiangning District	0.3936	Jiangning District	0.4894	Jiangning District	0.5426
Jiangyin City	0.3511	Jiangyin City	0.3830	Jiangyin City	0.4468	Jiangyin City	0.5213
Hanjiang District	0.3404	Binhu District	0.3511	Danyang City	0.4362	Binhu District	0.4894
Zhangjiagang City	0.3191	Gaogang District	0.3511	Binhu District	0.4149	Hanjiang District	0.4787
Jingkou District	0.3191	Zhangjiagang City	0.3404	Xinwu District	0.4149	Xinwu District	0.4681
Gaogang District	0.3191	Hanjiang District	0.3404	Huqiu District	0.4149	Jintan District	0.4681
Taixing City	0.3191	Jingkou District	0.3404	Zhangjiagang City	0.4149	Huishan District	0.4468
Danyang City	0.3085	Taixing City	0.3404	Qixia District	0.4043	Yixing City	0.4468

The node strength results show stronger spatial concentration (Table 5). Xuanwu District, Qinhuai District, and Gulou District (Nanjing) ranked among the top nodes for four consecutive years, while Yuhuatai District and Jiangning District also maintained relatively high levels across the four observations, indicating that Nanjing’s central urban area and its nearby county-level units have prominent advantages in the strength of potential innovation linkages. This is related to the combined effects of innovation capability and spatial proximity in the gravity model, reflecting the strong local agglomeration of high-intensity linkages in Nanjing’s central urban area. In 2023, Wuxi-related county-level units such as Binhu District, Liangxi District, Xinwu District, and Xishan District entered the top ten, indicating that the linkage strength of some nodes in the Suzhou–Wuxi–Changzhou area had improved. Overall, degree centrality and node strength reveal two different types of node functions: the former emphasizes wide-area connectivity, while the latter emphasizes the agglomeration capability of strong linkages.

Table 5. Top ten county-level units by node strength in Jiangsu’s potential innovation linkage network.

2020		2021		2022		2023	
County-Level Unit	Value	County-Level Unit	Value	County-Level Unit	Value	County-Level Unit	Value
Xuanwu District	1.0000	Xuanwu District	1.0000	Xuanwu District	1.0000	Xuanwu District	1.0000
Qinhuai District	0.9752	Qinhuai District	0.9810	Qinhuai District	0.9550	Qinhuai District	0.9640
Gulou District (Nanjing)	0.2119	Gulou District (Nanjing)	0.2103	Gulou District (Nanjing)	0.1926	Gulou District (Nanjing)	0.1931
Yuhuatai District	0.1037	Yuhuatai District	0.0966	Yuhuatai District	0.0934	Yuhuatai District	0.0925
Jiangning District	0.0704	Jiangning District	0.0713	Jiangning District	0.0699	Jiangning District	0.0787
Jianye District	0.0648	Jianye District	0.0616	Jianye District	0.0577	Binhu District	0.0710
Binhu District	0.0352	Binhu District	0.0429	Binhu District	0.0420	Jianye District	0.0609
Xiangcheng District	0.0322	Xiangcheng District	0.0385	Xiangcheng District	0.0410	Liangxi District	0.0599
Hanjiang District	0.0312	Liangxi District	0.0380	Gusu District	0.0387	Xinwu District	0.0464
Liangxi District	0.0305	Gusu District	0.0359	Wuzhong District	0.0360	Xishan District	0.0428

On this basis, the core–periphery model was used to analyze the overall structure of Jiangsu’s county-level innovation network. The results show that the network exhibited certain characteristics of core–periphery differentiation and hierarchical organization during the study period (Figure 6). It should be noted that the core–periphery model mainly calculates the coreness of each node. To improve the readability and interpretability

of the results, this study further classifies county-level units into the core layer, sub-core layer, transitional layer, and peripheral layer according to the magnitude and distribution characteristics of coreness.

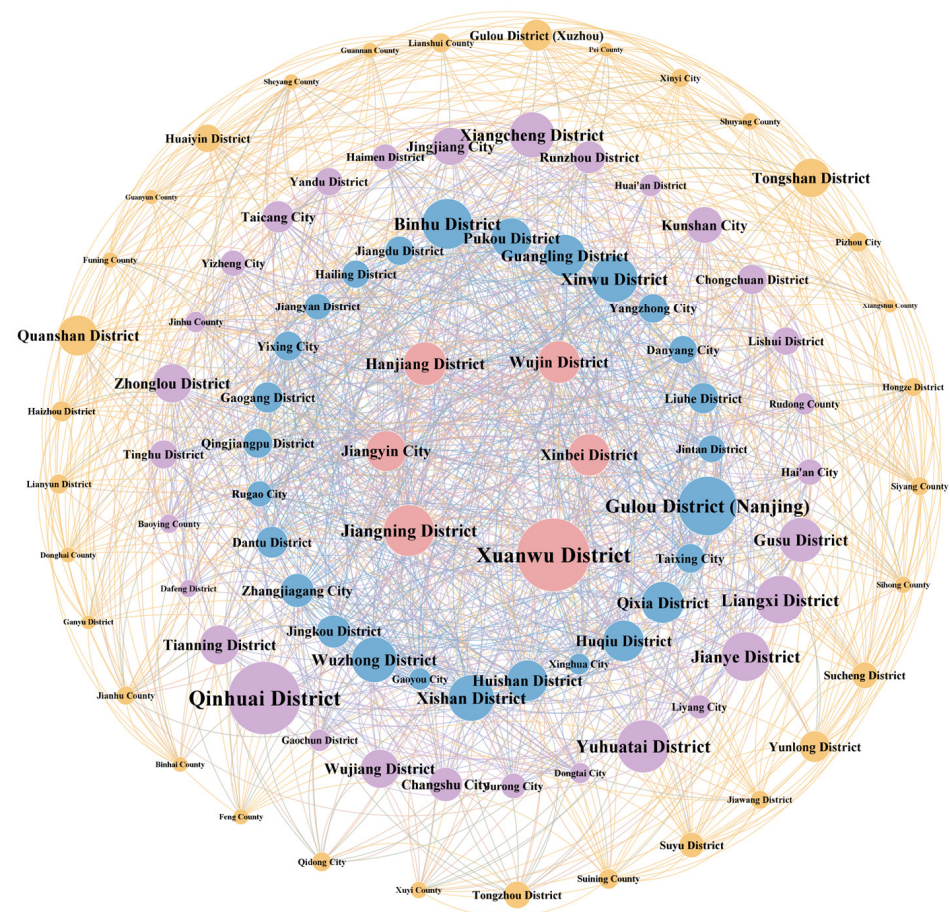


Figure 6. Core-periphery structure of the county-level potential innovation linkage network in Jiangsu Province, 2023. County-level units were grouped into core, sub-core, transitional, and peripheral layers using the Jenks natural breaks classification of coreness scores.

The classification results show that Wujin District, Jiangning District, Hanjiang District, Xinbei District, Jiangyin City, and Xuanwu District are located in the core layer, indicating that the core of the provincial innovation network is not dominated by a single administrative center, but is jointly constituted by county-level units with strong innovation capabilities in the Suzhou–Wuxi–Changzhou area, core county-level units in Nanjing, and connecting nodes in Central Jiangsu. Among them, Wujin District, Xinbei District, and Jiangyin City reflect the strong network connectivity foundation of the Suzhou–Wuxi–Changzhou area; Jiangning District and Xuanwu District demonstrate the structural embeddedness of the Nanjing block; and Hanjiang District indicates that selected units in Central Jiangsu have entered the highly embedded tier of the provincial network. This suggests that the core layer of Jiangsu’s county-level innovation network constitutes a multi-node relational core rather than a hierarchy radiating from a single administrative center.

From the perspective of the overall hierarchy, the sub-core layer further includes county-level units such as Binhu District, Gulou District (Nanjing), Huishan District, Zhangjiagang City, Xinwu District, Qixia District, Huqiu District, Guangling District, and Pukou District, indicating that highly embedded nodes in the provincial innovation network have expanded from the core layer toward the interior of Southern Jiangsu and parts of Central Jiangsu. By contrast, the transitional and peripheral layers are more

widely distributed in Northern Jiangsu and some peripheral counties, suggesting that although peripheral county-level units have been incorporated into the provincial potential innovation linkage network, their stable connections with the core layer remain relatively insufficient. Overall, Jiangsu's county-level innovation network is not a simple core–periphery dichotomy, but shows a gradient-based organizational structure characterized by multi-node support in the core layer, regional expansion in the sub-core layer, and weak embeddedness in the peripheral layer. This indicates that the expansion of the provincial innovation network mainly unfolds along existing highly embedded county-level units and system-supporting nodes, and has not yet formed a balanced pattern of network embeddedness across the whole province.

Overall, the node structure of Jiangsu's county-level innovation network is not dominated by a single type of node, but shows differentiated characteristics in which connection breadth, linkage strength, and structural embeddedness coexist. Nanjing's central urban area is more prominent in the agglomeration of strong linkages, while some county-level units in the Suzhou–Wuxi–Changzhou area show stronger advantages in wide-area connectivity and structural embeddedness. A few riverside and Central Jiangsu nodes also exhibit a certain hierarchical supporting role. These results indicate that the core position of a node in the provincial innovation network does not depend entirely on the innovation capability of the county-level unit itself, but is jointly shaped by the scope of node connections, linkage strength, and network embeddedness.

4.3. Identification of Key Nodes and Key Transmission Pathways

4.3.1. Identification of Key Nodes in the Potential Innovation Linkage Network

The preceding analysis identified structural hubs and hierarchical patterns in Jiangsu's innovation network based on node centrality and the core–periphery structure. However, structurally central nodes are not necessarily equivalent to structurally important nodes in the model-derived network. Some nodes may have high centrality but remain embedded mainly in local networks, whereas nodes located at cross-regional connection positions may play a more important bridging role in maintaining cross-regional connectivity [42]. Therefore, key node identification should consider not only the static connection position of a node, but also its comprehensive influence on network connectivity maintenance and simulated structural reach. Based on this logic, this study uses the GNR composite score as the basis for identifying key nodes and further analyzes their functional differences by combining the innovation capability index, normalized degree centrality, and SI-simulated structural reach.

The identification of key nodes is based on the largest connected component of the Top-3 backbone network. Since the Top-3 network contains a small number of local disconnections, GNR is calculated only within the largest connected component to ensure the comparability of node indicators, while nodes in smaller components are recorded separately. In Table 6, the GNR composite score represents the overall criticality of a node, normalized degree centrality reflects the level of direct linkages, and SI-simulated structural reach indicates the number of nodes potentially reachable under standardized simulation conditions, while the innovation capability index represents the local innovation foundation of each county-level unit. Thus, key node identification is placed within an integrated analytical framework of “node attributes–structural position–simulated structural reach”, rather than relying solely on centrality rankings.

Table 6. Key nodes and their structural attributes in Jiangsu’s potential innovation linkage network.

Rank	County-Level Unit	GNR Composite Score	Normalized Degree Centrality	SI-Simulated Structural Reach	Innovation Capability Index
1	Xuanwu District	1.000	1.000	68.768	0.400
2	Jiangning District	0.917	0.818	72.968	0.620
3	Hanjiang District	0.729	0.636	78.836	0.292
4	Wujin District	0.661	0.636	70.788	0.539
5	Qingjiangpu District	0.648	0.636	60.464	0.199
6	Sucheng District	0.557	0.545	45.556	0.197
7	Jingkou District	0.556	0.545	76.844	0.153
8	Qixia District	0.550	0.545	71.204	0.331
9	Wuzhong District	0.545	0.545	52.540	0.487
10	Chongchuan District	0.545	0.545	62.208	0.299
11	Zhangjiagang City	0.545	0.545	64.068	0.332
12	Huishan District	0.545	0.545	62.884	0.312
13	Kunshan City	0.545	0.545	54.928	0.571
14	Xiangcheng District	0.545	0.545	54.396	0.343
15	Jiangyan District	0.467	0.455	77.620	0.210

As shown in Table 6, the identified key nodes exhibit distinct combinations of innovation capability, normalized degree centrality, and SI-simulated structural reach. Xuanwu District is characterized by strong direct connectivity, whereas Jiangning District combines a strong innovation foundation with substantial network-organizing capacity. Hanjiang District, despite its more moderate innovation capability, exhibits comparatively high simulated structural reach, indicating that node criticality is shaped not only by innovation capability but also by network position and cross-regional connectivity [43].

Based on Table 6, the key nodes can be further classified into three main functional types: core-organizing nodes, system-supporting nodes, and connector nodes. The first type consists of core-organizing nodes, mainly including Xuanwu District and Jiangning District. These nodes perform prominently in terms of composite score, normalized degree centrality, or innovation capability, and undertake core organization and resource aggregation functions in the provincial innovation network. The second type consists of system-supporting nodes, mainly including Wujin District, Qixia District, Wuzhong District, Chongchuan District, Zhangjiagang City, Huishan District, Kunshan City, Xiangcheng District, and Jingkou District. Although these nodes do not necessarily play a significant role in maintaining overall connectivity, they have certain advantages in normalized degree centrality, simulated structural reach, or innovation capability. They mainly support linkage maintenance, local coordination, and block-level integration within Nanjing, Southern Jiangsu, and riverside areas. For example, Kunshan City has an innovation capability index of 0.571, second only to Jiangning District, but its GNR composite score does not rank among the very top nodes. This suggests that a node’s own innovation capability is not fully consistent with its structural criticality in the backbone network; within this network, Kunshan City functions more as a high-innovation supporting node within the Southern Jiangsu block.

The third type consists of connector nodes, mainly including Hanjiang District, Qingjiangpu District, Sucheng District, and Jiangyan District. These nodes do not have particularly strong innovation capability, but their inclusion in the key node sequence indicates that they have been embedded in the provincial innovation backbone network and have structural significance in linkage access, local maintenance, or cross-regional con-

nection. Among them, Hanjiang District has relatively strong SI-simulated structural reach and contributes to maintaining connectivity, making it a representative node of this type with clear connector characteristics. Qingjiangpu District, Sucheng District, and Jiangyan District function more as local supporting nodes through which Central and Northern Jiangsu are embedded in the provincial innovation network, and should not be simply interpreted as province-wide core-organizing nodes. In other words, the value of connector nodes lies mainly in enhancing the connection between peripheral areas and the backbone network, rather than replacing core nodes in performing global organizing functions.

From the perspective of spatial distribution, different types of key nodes show clear regional differentiation. Core-organizing nodes are mainly concentrated in Nanjing-related county-level units, system-supporting nodes are mostly distributed in Southern Jiangsu and riverside areas, while connector nodes mainly appear in the transitional zones of Central and Northern Jiangsu. This indicates that the key nodes of Jiangsu's innovation network present a hierarchical structure of "core organization–system support–bridging embeddedness." Therefore, the role of county-level units in the provincial innovation network does not depend solely on their own innovation capability, but is jointly shaped by network position, spatial location, and cross-regional linkage functions. This functional differentiation suggests that the operation of the provincial innovation system is not dominated by a single core, but depends on multi-level coordination among core, supporting, and connector nodes.

4.3.2. Identification of Key Transmission Pathways

Building on the identification of key nodes in the innovation network, this study further extracts the key pathways among these nodes and constructs a key pathway subnetwork of Jiangsu Province's innovation network. This helps reveal, from a structural-connectivity perspective, the main organizational channels and spatial patterns of potential linkages within provincial space. Compared with node centrality analysis, which mainly characterizes the structural position of nodes in the overall network, key pathway identification places greater emphasis on structurally important potential channels among different county-level units, thereby further explaining how these linkages connect different territorial units and regional blocks within the provincial potential innovation linkage network. Figure 7 is drawn based on the Top-5 backbone linkage network, where line width indicates the strength of potential innovation linkages and node size represents the GNR composite score. Figure 7 shows that key innovation pathways in Jiangsu Province are not evenly distributed across the whole province, but instead exhibit a pathway organization pattern characterized by "intra-cluster reinforcement–corridor-based continuation–short-chain embedding."

In terms of pathway morphology, high-intensity key pathways are first concentrated within the Nanjing core area and the Suzhou–Wuxi–Changzhou block with strong innovation capabilities, although their organizational logics differ. The Nanjing core area constitutes an important organizational block of provincial innovation linkages, and its key pathways show a relatively clear pattern of "core organization–radial external linkage." Dense linkages are formed among Xuanwu District, Jiangning District, and surrounding central urban nodes, with external pathways extending toward Zhenjiang, Yangzhou, and other directions. This indicates that Nanjing-related county-level units are not only agglomeration areas of local high-intensity linkages, but also important starting points for organizing provincial innovation linkages and connecting outward. Their role lies in transforming high-density linkages within the block into pathway channels oriented toward other areas of the province.

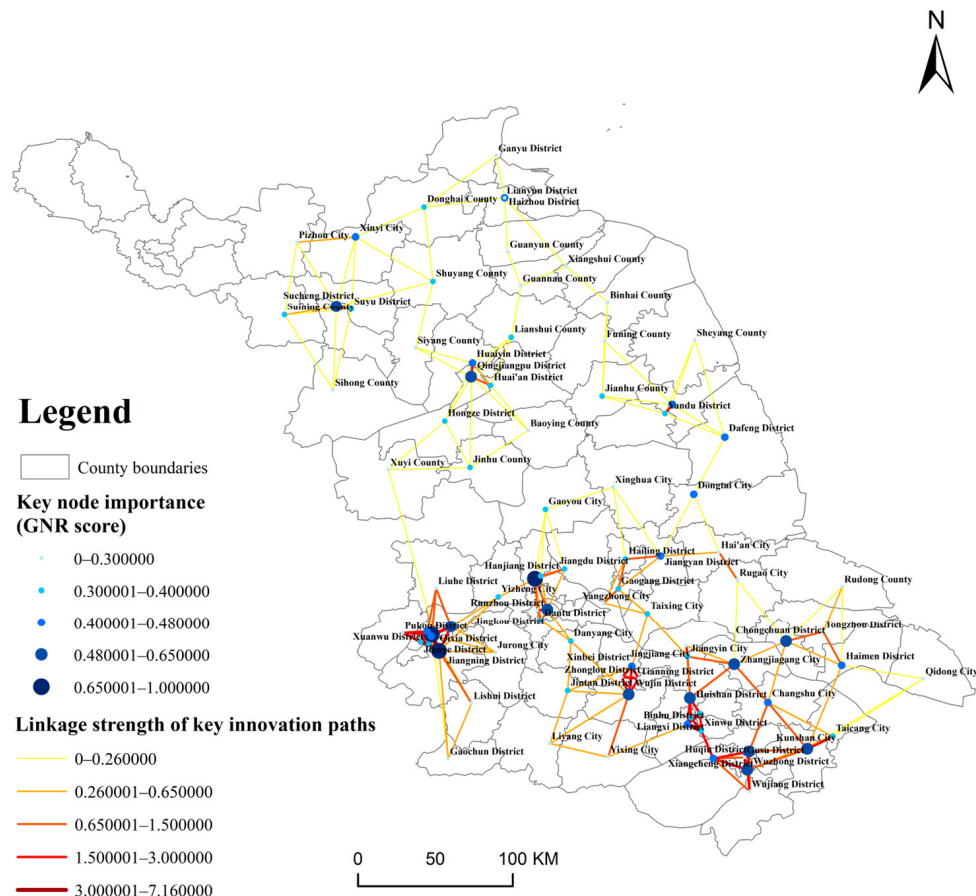


Figure 7. Key transmission pathways identified from the model-derived potential innovation linkage network in Jiangsu Province.

Different from the organizational and outward-linking characteristics of the Nanjing core area, the Suzhou–Wuxi–Changzhou block with strong innovation capabilities is more characterized by multi-node coordination and continuous intercity linkage. Linkages among relevant county-level units in Changzhou, Wuxi, and Suzhou are relatively dense, with Wujin District, Xinbei District, Binhu District, Xinwu District, Huishan District, Wuzhong District, Kunshan City, Zhangjiagang City, Xiangcheng District, and other nodes jointly forming a high-intensity linkage network. This block is not dominated by a single core node; rather, it is jointly supported by multiple nodes with strong innovation capabilities and forms a continuous connection structure through intercity linkages, reflecting functions of horizontal coordination, block-based connection, and pathway extension. More specifically, the internal structure of the Suzhou–Wuxi–Changzhou block with strong innovation capabilities is not a simple linear sequence, but shows a certain degree of multi-point interweaving and localized closed linkage. Multidirectional linkages are formed among Wujin District and Xinbei District in Changzhou; Binhu District, Xinwu District, and Huishan District in Wuxi; and Wuzhong District, Huqiu District, Xiangcheng District, Kunshan City, Changshu City, Zhangjiagang City, and Taicang City in Suzhou. Compared with a single-route configuration, this multi-point interwoven structure is closer to internal cyclical reinforcement within the block, indicating that innovation linkages in the Suzhou–Wuxi–Changzhou area have strong horizontal coordination and a certain degree of network redundancy. In other words, even if some nodes are not prominent in terms of connectivity-maintenance indicators, they may still play a stable supporting role within the region through multi-path connections.

Cross-regional connectivity is organized segment by segment through riverside and intercity nodes, showing a strong corridor-based continuation pattern. The linkage between the Nanjing core area and the Suzhou–Wuxi–Changzhou block is not formed through a large number of long-distance direct connections, but is instead connected stepwise through nodes in Zhenjiang, Changzhou, Wuxi, and other areas. Jingkou District, Dantu District, Danyang City, Xinbei District, Wujin District, Jiangyin City, Huishan District, and other nodes form a relatively continuous pathway chain along the Nanjing–Zhenjiang–Changzhou–Wuxi direction. This indicates that cross-block linkages are not completed directly by a single strong node, but are maintained by a group of continuous nodes that jointly support pathway accessibility.

By contrast, key pathways in Central and Northern Jiangsu are more characterized by localized embedding and short-chain access. Although Huai'an, Suqian, Yancheng, Lianyungang, and other areas show several backbone linkages, these linkages are mostly concentrated within local clusters or between neighboring nodes, and their linkage strength and continuity are clearly weaker than those in the Nanjing core area and the Suzhou–Wuxi–Changzhou block. The emergence of nodes such as Qingjiangpu District, Huaiyin District, Sucheng District, Suyu District, Haizhou District, Donghai County, Tinghu District, and Dafeng District indicates that Central and Northern Jiangsu have been embedded into the backbone linkage structure through selected nodes. However, this embedding is mainly manifested as node-based access and local network maintenance, and has not yet developed into stable, continuous, high-intensity cross-regional linkage corridors.

Overall, the key pathways of Jiangsu Province's innovation network show clear spatial unevenness and hierarchy, forming a composite pathway configuration in which organizational agglomeration, block-based continuation, and peripheral embedding coexist. The Nanjing core area mainly undertakes the functions of pathway organization and external linkage guidance; the Suzhou–Wuxi–Changzhou block with strong innovation capabilities supports intercity linkage through multi-node coordination; riverside and intercity nodes play a staged connecting role; and Central and Northern Jiangsu are mainly embedded in the backbone network through local clusters and short chains. This indicates that Jiangsu's model-derived potential innovation linkage network exhibits a spatially selective and hierarchical configuration shaped by core nodes, linkage corridors, transitional locations, and local clusters [44].

4.4. Distinctiveness and Robustness Analyses

4.4.1. Distinctiveness Between Innovation Capability and Network Position

Because the potential innovation linkage network is jointly constructed from county-level innovation capability and geographical distance, its derived network indicators may partly reproduce the ranking patterns of innovation capability. To assess whether the network analysis merely restates differences in innovation capability, Spearman's rank correlation analysis was used to examine the relationships between innovation capability and four network-position indicators: degree in the backbone network, weighted betweenness centrality, SI-simulated structural reach, and GNR composite score. The 95% confidence intervals for the correlation coefficients were estimated using 1000 bootstrap resamples, and the Benjamini–Hochberg procedure was applied to control the false discovery rate associated with multiple testing.

As shown in Table 7, innovation capability was most strongly associated with degree in the backbone network ($\rho = 0.521$), followed by GNR composite score ($\rho = 0.358$) and weighted betweenness centrality ($\rho = 0.272$), whereas its association with SI-simulated structural reach was negligible and statistically nonsignificant ($\rho = 0.012$). Thus, county-level units with stronger innovation capability generally form more backbone linkages.

However, whether a unit occupies an intermediary position along important network paths, attains greater structural reach, or holds a structurally important network position also depends on geographical distance, the characteristics of surrounding nodes, and the configuration of its linkages within the wider network. Overall, innovation capability provides an important basis for the formation of potential linkages but does not fully explain a node's network position or structural role. Network analysis therefore does not simply reproduce innovation capability rankings; rather, it provides complementary insights into differences in relational structure and network position among county-level units.

Table 7. Correlations between innovation capability and network-position indicators.

Network-Position Indicator	Sample Size	Spearman's ρ	Bootstrap 95% CI	FDR-Adjusted p -Value
Degree in the backbone network	95	0.521	[0.349, 0.657]	<0.001
Weighted betweenness centrality	95	0.272	[0.071, 0.445]	0.012
SI-simulated structural reach	95	0.012	[−0.165, 0.218]	0.909
GNR composite score	88	0.358	[0.159, 0.533]	0.001

Note: GNR composite score was calculated only for the 88 county-level units included in the largest connected component of the Top-3 backbone network. SI-simulated structural reach denotes the average number of nodes reachable from a given node under standardized simulation conditions and does not represent actual flows of innovation factors.

4.4.2. Sensitivity Analysis of Network Binarization Thresholds

To assess the sensitivity of the network results to the choice of binarization threshold, this study uses the 75th, 80th, and 85th percentiles of the pooled distribution of potential innovation linkage strengths over 2020–2023 as fixed thresholds applied consistently across all years. The P80 threshold is used as the baseline. Robustness is evaluated by comparing overall network metrics, node degree rankings, and the composition of the top-10 highly connected node sets across the three threshold scenarios (Table 8).

Table 8. Consistency of network metrics and node rankings across alternative binarization thresholds.

Threshold Scenario	Network Density (2020–2023)	Global Efficiency (2020–2023)	Average Clustering Coefficient (2020–2023)	Relative Size of the Largest Connected Component	Spearman's ρ for Degree Rankings Relative to P80	Jaccard Similarity of Top-10 Node Sets Relative to P80
P75	0.207–0.294	0.465–0.554	0.708–0.760	1.000	0.982 (0.978–0.985)	0.703 (0.667–0.786)
P80 (baseline)	0.163–0.241	0.411–0.498	0.678–0.715	1.000	1.000	1.000
P85	0.123–0.183	0.308–0.422	0.652–0.664	0.821–0.989	0.970 (0.961–0.982)	0.720 (0.667–0.833)

Note: P80 denotes the baseline scenario. Network metrics are reported as ranges over 2020–2023. Spearman's ρ and Jaccard similarity are reported as four-year means, with the corresponding annual ranges shown in parentheses. The top-10 node sets include all nodes tied at the ranking cutoff.

As the binarization threshold increases, network density, global efficiency, and the relative size of the largest connected component decline, as expected when lower-strength potential linkages are progressively excluded. Despite the resulting differences in network sparsity, all three threshold specifications yield the same direction of temporal change: network density and global efficiency increase over 2020–2023, while the average clustering coefficient shows an overall upward trend. These consistent patterns indicate that the inferred expansion of potential linkages, improvement in network-wide accessibility, and strengthening of local clustering are not specific to the P80 threshold.

At the node level, the overall degree rankings remain highly stable, whereas the top-10 node sets exhibit substantial but incomplete overlap. Relative to the P80 baseline, the mean Spearman's ρ values for degree rankings are 0.982 under P75 and 0.970 under P85. The corresponding mean Jaccard similarities of the top-10 node sets are 0.703 and 0.720, respectively. Threshold changes therefore primarily affect peripheral linkages and nodes

close to the top-10 ranking cutoff, without materially altering the overall degree-ranking pattern or the principal group of highly connected nodes.

Under the P85 specification, the relative size of the largest connected component is smaller in the earlier years of the study period, indicating that the inclusion of peripheral nodes in the main connected structure is more sensitive to a stricter threshold. This sensitivity does not alter the overall temporal direction of the network metrics. The main findings concerning the expansion of potential linkages among county-level units, increasing global efficiency, and strengthening local clustering are therefore robust across the three binarization thresholds considered.

4.4.3. Robustness of Key-Node and Pathway Identification

Because both key-node identification and key transmission pathway identification rely on Top-M sparsified networks, their results may be sensitive to the choice of M [45]. Different baseline specifications are used for the two analyses. The Top-3 backbone network serves as the baseline for key-node identification because a relatively sparse specification more clearly differentiates structurally important nodes. The Top-5 network serves as the baseline for key transmission pathway identification because retaining additional high-strength cross-county linkages improves pathway continuity and spatial interpretability. To assess whether the findings are driven by a single parameter choice, three adjacent specifications—Top-3, Top-4, and Top-5—are compared. Consistency across specifications is evaluated using the numbers of overlapping and union elements and the corresponding Jaccard similarities for node and edge sets [46].

The robustness of key-node identification is assessed by comparing the top-10 node sets across the alternative Top-M specifications. As shown in Table 9, the Jaccard similarity between the Top-3 and Top-4 specifications ranges from 0.429 to 0.539 over 2020–2023, whereas that between the Top-4 and Top-5 specifications ranges from 0.667 to 1.000. The exact membership of the top-10 set is therefore moderately sensitive to the Top-M specification, particularly for nodes close to the ranking cutoff. However, the higher overlap between the Top-4 and Top-5 results indicates that the key-node set becomes more stable when additional high-strength linkages are retained. Accordingly, the analysis emphasizes the relative structural roles and functional characteristics of key nodes rather than their exact ordinal rankings.

Table 9. Robustness of key-node identification across adjacent Top-M sparsification specifications.

Year	Comparison Scheme	Overlapping Nodes	Union Nodes	Jaccard Similarity
2020	Top-3 vs. Top-4	7	13	0.539
2020	Top-4 vs. Top-5	8	12	0.667
2021	Top-3 vs. Top-4	7	13	0.539
2021	Top-4 vs. Top-5	10	10	1.000
2022	Top-3 vs. Top-4	6	14	0.429
2022	Top-4 vs. Top-5	8	12	0.667
2023	Top-3 vs. Top-4	6	14	0.429
2023	Top-4 vs. Top-5	9	11	0.818

Note: Overlapping nodes refer to the nodes appearing in both top-10 key-node sets under two adjacent Top-M specifications. Jaccard similarity is calculated as the number of overlapping nodes divided by the number of nodes in the union set; higher values indicate greater consistency in key-node identification.

The robustness of key transmission pathway identification is evaluated by comparing pathway edge sets across alternative Top-M networks while holding the anchor nodes constant. As shown in Table 10, the Jaccard similarity between the Top-3 and Top-4

specifications is 0.818 in each year, while that between the Top-4 and Top-5 specifications is 0.905 in each year. These values indicate substantial overlap in the backbone-pathway edge sets across parameter specifications. Although the pathway results are descriptively more stable than the key-node sets, the two comparisons involve different types of sets and should not be interpreted as directly equivalent. Overall, changes in Top-M affect the exact membership of the top-10 key-node set more than the broad configuration of the key transmission pathways. The main structural pattern and the identified key transmission pathways are therefore reasonably robust across the specifications considered, whereas the precise ranking and inclusion of individual key nodes should be interpreted with caution.

Table 10. Robustness of pathway identification across adjacent Top-M sparsification specifications.

Year	Comparison Scheme	Overlapping Edges	Union Edges	Jaccard Similarity
2020	Top-3 vs. Top-4	18	22	0.818
2020	Top-4 vs. Top-5	19	21	0.905
2021	Top-3 vs. Top-4	18	22	0.818
2021	Top-4 vs. Top-5	19	21	0.905
2022	Top-3 vs. Top-4	18	22	0.818
2022	Top-4 vs. Top-5	19	21	0.905
2023	Top-3 vs. Top-4	18	22	0.818
2023	Top-4 vs. Top-5	19	21	0.905

Note: Overlapping edges refer to the edges shared by the backbone-pathway edge sets under two adjacent Top-M specifications. Jaccard similarity is calculated as the number of overlapping edges divided by the number of edges in the union set. Anchor nodes are held constant across specifications; therefore, identical Jaccard values across years do not imply identical pathway compositions.

5. Discussion

5.1. Beyond Innovation Capacity: Differentiated County Roles in Innovation Networks

The results indicate that innovation capability and network position represent related but distinct dimensions of provincial innovation systems. Although counties with stronger innovation capability generally exhibit higher network connectivity, capability advantages alone cannot fully explain structural importance within potential innovation linkage networks. The correlation analysis shows that innovation capability is more strongly associated with direct connectivity, whereas its relationships with weighted betweenness centrality, GNR composite scores, and SI-based structural reach are comparatively weaker (Table 7). This divergence suggests that network positions reflect relational dimensions of innovation organization beyond local innovation capacity.

The findings extend innovation network analysis beyond capability-based interpretations by highlighting the role of relational embeddedness. Counties with comparable innovation capabilities may occupy different network positions, as reflected by the differentiated structural roles identified through GNR analysis (Table 6), while some moderately capable counties may obtain greater structural influence through their positions within interregional connections. Therefore, network significance is not simply a spatial reflection of innovation capacity but also depends on how territorial units are embedded within broader relational configurations [47]. This perspective reveals that provincial innovation systems are organized through differentiated territorial roles, including innovation concentration, regional support, and structural bridging.

The county-level perspective is particularly important for identifying such differentiated roles that may be obscured by higher-level aggregation. By treating counties as relational nodes, this study demonstrates that territorial importance is shaped not only by the amount of innovation resources accumulated locally but also by their positions

within the wider network structure. These findings provide a relational perspective for understanding provincial innovation organization and suggest that regional innovation development requires attention not only to capability enhancement but also to the coordination of network relationships.

5.2. Relational Patterns and Potential Backbone Pathways of the Provincial Innovation System

The results reveal that potential innovation linkages exhibit a structured spatial configuration rather than a random distribution, as demonstrated by the evolution of network structures and the spatial organization of key linkages (Figures 5–7). Although geographical proximity provides an important spatial constraint, the observed network structure indicates that connectivity is further differentiated by the relational positions of counties within the broader system. Therefore, provincial innovation networks should be interpreted as relational configurations shaped by the interaction between node attributes, spatial constraints, and network organization, rather than as simple outcomes of proximity or capability differences.

Three relational patterns characterize the organization of the provincial innovation network. First, cluster-based reinforcement reflects the concentration of dense linkages among geographically and functionally related counties, where regional advantages are associated with stronger internal connectivity within innovation clusters. Second, corridor-based connectivity highlights the role of intermediate counties that connect spatially separated clusters and maintain continuity across the provincial network. The identified backbone pathways further indicate that these intermediate nodes occupy important bridging positions between major innovation regions (Figure 7). Third, peripheral embedding describes how less-central counties participate in the broader network through connections with adjacent clusters rather than direct integration into dominant core areas. Together, these patterns suggest that provincial innovation networks are sustained not only by highly developed core regions but also by intermediate and peripheral nodes that contribute to network accessibility and structural continuity.

The identification of potential backbone pathways further demonstrates that network organization does not fully correspond to innovation capability rankings or administrative hierarchy. Counties located in bridging positions may achieve greater structural significance by connecting different regional blocks and maintaining potential relational channels across spatial boundaries (Figure 7). This finding highlights the structural contribution of intermediate nodes and extends understanding of regional innovation networks by emphasizing the importance of relational positions in shaping network organization. However, these pathways represent model-derived potential connectivity rather than directly observed knowledge diffusion, technological cooperation, or innovation resource flows.

5.3. Network-Oriented Governance Implications for Provincial Innovation Systems

The differentiated network structures identified in this study suggest that provincial innovation governance should move beyond a purely capability-oriented approach toward a network-oriented perspective. The findings indicate that improving local innovation capacity does not necessarily translate into stronger system-level connectivity, because territorial units perform different structural functions within the broader innovation network. Therefore, governance strategies should consider not only the accumulation of innovation resources but also the relational positions through which these resources are connected and organized.

From this perspective, governance priorities should be aligned with the structural roles identified in the network. Core nodes may focus on strengthening coordination and knowledge organization functions to extend their network effects, while transitional

nodes require support for maintaining cross-regional connections and improving linkage continuity. Peripheral areas may benefit from enhancing local innovation foundations and strengthening integration with surrounding networks rather than directly replicating the development trajectories of core regions. Such differentiated approaches may facilitate a more balanced and interconnected provincial innovation system by recognizing the complementary functions of heterogeneous territorial units.

The identified network structure also provides implications for resilience-oriented governance. Rather than representing realized resilience, the results identify structural conditions that may support adaptive capacity. Dense clusters may contribute to structural cohesion, while diversified connections and bridging positions may provide alternative relational channels within the network. However, because this study does not examine specific disruptions, recovery processes, or dynamic responses to external shocks, these implications should be interpreted as potential resilience-supporting conditions rather than direct evidence of resilience outcomes.

5.4. Limitations and Future Research

Several limitations should be acknowledged when interpreting the findings of this study. First, the potential innovation linkage network constructed in this study is based on county-level innovation capability and geographical distance. Therefore, it captures the structural possibilities of regional connectivity under spatial constraints rather than directly observed innovation interactions. Future research could incorporate empirical interaction data, such as inter-firm collaboration, knowledge exchange, or technology-related linkages, to further examine the correspondence between potential network structures and realized innovation relationships.

Second, the network construction relies on a consistent threshold strategy to ensure comparability across different years. While this approach facilitates the identification of longitudinal structural changes, it may influence the representation of weak ties and peripheral connections. Future studies could further assess the robustness of identified patterns by comparing alternative network construction approaches, including weighted networks, adaptive thresholds, and backbone extraction methods.

Third, the temporal and spatial scope of this study limits the interpretation of long-term innovation network evolution. The four-year observation period captures stage-specific structural characteristics but cannot fully reveal persistent evolutionary trajectories or long-term transformation processes. Moreover, focusing on Jiangsu Province may not fully capture cross-regional linkages within broader innovation systems. Future research could extend the temporal scale and adopt multi-scalar perspectives to investigate how innovation networks evolve across different spatial levels.

6. Conclusions

Drawing on county-level innovation capability assessment, gravity-model estimation of potential innovation linkages, and the identification of key nodes and key transmission pathways, this study examined the stage-specific organization of Jiangsu's provincial innovation system during 2020–2023 from the perspectives of innovation foundations, network structure, and relational connectivity.

County-level innovation capability increased throughout the study period, while the overall spatial differentiation pattern remained relatively stable. Changes were primarily characterized by the upgrading of selected county-level units, the strengthening of transitional areas, and enhanced coordination among neighboring units rather than by a broad expansion of high-capability areas. These findings suggest that regional innovation development proceeded through selective upgrading and localized restructuring within

an established spatial hierarchy, rather than through a fundamental reconfiguration of the existing innovation landscape. The county-level perspective further reveals heterogeneous territorial conditions among urban cores, industrial-platform areas, transitional zones, and peripheral counties that may be obscured in more aggregated analyses.

The potential innovation linkage network became increasingly connected, as reflected by the increases in network density, average degree, global efficiency, and clustering coefficient. However, enhanced connectivity did not automatically translate into a more balanced network structure. Instead, network evolution was characterized by selective reinforcement around established innovation centers, while transitional counties gradually strengthened their embeddedness through differentiated relational roles. This finding indicates that provincial innovation networks evolve through uneven integration processes, where connectivity expansion and structural concentration occur simultaneously.

The key-node analysis further demonstrates that innovation capability and network position are complementary but non-equivalent dimensions of regional innovation systems. Structurally influential counties were not necessarily those with the highest innovation capability levels, but those occupying important relational positions as core-organizing, system-supporting, or connector nodes. By incorporating network perspectives, this study reveals relational attributes—including embeddedness, bridging capacity, and structural accessibility—that cannot be captured through capability-based evaluation alone. This highlights the importance of examining not only where innovation resources are concentrated but also how territorial units are connected within broader innovation systems.

The identification of potential backbone pathways further shows that provincial innovation connectivity is organized through multiple relational configurations, including reinforcement within innovation clusters, continuity through intercity corridors, and embedding of peripheral areas through short relational chains. Rather than following a simple diffusion process from dominant centers, provincial innovation networks are shaped by interactions among core nodes, intermediate connectors, and localized clusters. This finding illustrates the value of county-level network analysis in identifying transitional and bridging territories whose systemic importance may remain overlooked in conventional spatial assessments.

These findings imply that provincial innovation governance should move beyond a purely capability-oriented approach toward a network-oriented perspective. Rather than applying uniform development strategies across regions, governance interventions should recognize differentiated territorial roles and strengthen the complementary functions of core nodes, bridging counties, and weakly embedded areas. Because the constructed network is derived from innovation capability and geographical distance, the identified structures and pathways represent model-estimated relational potential rather than directly observed knowledge flows, technological cooperation, or innovation diffusion. Within this interpretive boundary, this study demonstrates how county-level relational analysis can provide structural insights for understanding innovation organization and supporting more coordinated and adaptive regional innovation governance.

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