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How Does Digital Transformation Affect Cross-Regional Collaborative Innovation: Evidence from A-Share Listed Firms

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Abstract

This study utilizes digital transformation and patent data from A-share listed companies on the Shanghai and Shenzhen stock exchanges in China between 2011 and 2021 to examine the influence of digital transformation on the quality of cross-regional collaborative innovation. The findings reveal that the cooperative innovation network exhibits pronounced small-world characteristics. In terms of spatio-temporal evolution, China's urban collaborative innovation network demonstrates a notable quadrilateral spatial structure and has evolved toward a multicenter pattern. Moreover, the advancement of digital transformation positively contributes to both the quality and quantity of cross-regional cooperative innovation. By enhancing the relational embeddedness among cities, digital transformation facilitates improved outcomes in collaborative innovation. Furthermore, when the volume of digital patent applications surpasses a certain threshold, its positive effect on the quality of cross-regional collaborative innovation accelerates. These results provide empirical evidence from a major emerging economy, offering insights that can inform policies and strategies in other regions undergoing digital transition. The mechanisms identified, such as network structure evolution and relational embeddedness, contribute to a broader understanding of how digital transformation shapes innovation dynamics across geographical boundaries in a globalized knowledge economy.

Keywords: digital transformation; cross-regional innovation; cooperation network; innovative quality; listed companies in Shanghai and Shenzhen



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1. Introduction

Accompanied by the new wave of technological revolution and industrial transformation, digital transformation is reshaping the global economic landscape. In 2023, the scale of the digital economy of major economies around the world reached up to USD 33 trillion, accounting for over 60% of GDP, and it has become a pivotal force driving global economic development [1]. The world is entering an era of digital and intelligent economy driven by artificial intelligence. It is estimated that by 2030, the contribution of artificial intelligence to the global economy will exceed 22.3 trillion US dollars, accounting for 3.7% of global GDP. In this process, all countries have actively laid out digital strategies to promote the

deep integration of digital technology with the real economy. The EU promotes technological sovereignty and green digital transformation through the Digital Decade Policy Plan (DDPP). The United States is also strengthening digital infrastructure construction and innovation ecology cultivation in several technology and industrial policies. Meanwhile, China's digital economy has become an emerging driving force of economic development, and its contribution rate to the gross domestic product (GDP) ranked second in the world, only after the United States [2]. These reflect the rapid rise and active adaptation of emerging economies in the wave of digitalization. The development of China's digital economy has moved from the system construction stage during the 14th Five-Year Plan period to a new stage of high-quality development with intelligent empowerment as the core and collaborative innovation. The 2026 Government Work Report of China proposed the core deployment of building a new form of smart economy. This reflects that the national level is improving the digital governance system and breaking down barriers to the circulation of data elements. Also, it is important to promote the deep integration of science and technology and industry as well as to lay a solid institutional and technological foundation for regional cooperation and innovation. In this situation, enterprises are the core micro-subjects of economic operation, facing the strategic requirements of the 15th Five-Year Plan for the market-oriented allocation of data elements in China. The mining, integration, and application of data elements in the whole innovation chain by enterprises is not only an inevitable measure to implement for national strategic deployment but also a key path to drive the transformation of the innovation paradigm and improve the quality and efficiency of regional cooperative innovation.

Digital transformation not only significantly promotes economic growth but also creates basic conditions for transnational and cross-regional innovation cooperation. In turn, it will promote the evolution of the global innovation system to higher quality. In 2023, the number of patent grants in China reached 921,000, a year-on-year increase of 15.3%, ranking it the country with the largest number of patents in the world [3]. It also signals that the global innovation landscape is undergoing profound changes. The wide application of digital technology has promoted the formation of a cross-regional and cross-industrial collaborative innovation system. More and more countries are focusing on the transformation of innovation from quantitative expansion to qualitative advancement. The interaction and collaboration among innovation subjects and the continuous improvement in regional innovation networks help to shape the complementarity pattern of regional innovation resources [4]. At the same time, the continuous output of high-quality innovation achievements has injected endogenous growth impetus into the development of the digital economy. In the face of the external environment of increasing technical complexity and shortening technology iteration cycle, enterprises adopt an open innovation strategy to strengthen their own technological capabilities and knowledge reserves with the help of external innovation resources and maintain core competitive advantages [5]. Digital transformation and innovation form a benign interactive mechanism of mutual promotion and collaborative evolution. Therefore, the two-way promotion relationship between digital economy and innovation quality is forming a virtuous cycle on a global scale. Together, these forces are driving the transformation of the world economy to an innovation-driven and high-quality development paradigm.

In this context, based on the macro perspective of global digital transformation, this study aims to systematically analyze the driving mechanism and reshaping logic of digital technology on collaborative innovation and then discuss how to promote the collaborative improvement in innovation quality while the innovation scale expands rapidly. Existing research mostly studies the development of the digital economy based on the statistical data of specific areas, and some scholars also examine the openness of cross-regional

innovation based on national or regional enterprise samples, such as China's A-share listed companies or manufacturing enterprises. Based on this, this study extends the innovation behavior at the enterprise level to the city level to reveal the spatial pattern and quality characteristics contained in cross-regional collaborative innovation. In terms of the measurement of collaborative innovation, compared with traditional research, which generally uses the number of common patent applications as the measurement index, this study innovatively introduces the number of patent citations as the proxy variable of innovation quality. It also provides a more accurate empirical basis for revealing the internal mechanism of the dual improvement in innovation level and innovation quality driven by digital technology. By systematically constructing the theoretical analysis framework and action path of digital transformation to promote the quality improvement in cross-regional collaborative innovation, this study aims to provide an explanatory perspective for understanding the new characteristics and trends of innovation development in the global digital wave. The marginal contribution of this paper is mainly reflected in three aspects. Firstly, in the analysis of samples, the enterprise innovation behavior is spatialized to the city level, which expands the spatial analysis dimension of cross-regional innovation research. Secondly, in terms of the measurement method, the number of patent citations is used to replace the traditional number of patent applications, which is closer to the essential connotation of innovation quality. Thirdly, in terms of mechanism identification, this study deeply explores the multiple paths through which digital transformation enables the quality improvement in collaborative innovation. It makes up for the deficiency that comes from existing research mainly focusing on the quantity effect and ignoring the quality effect. At the practical level, the research conclusions of this paper can provide decision-making reference at the micro level for enterprises to formulate scientific innovation and digital transformation strategies in the digital wave. It also helps enterprises rationally identify and deal with potential risks and realize the benign interaction between technology empowerment and strategic response. At the macro level, this study provides comparable international experience and policy enlightenment for policymakers around the world to promote the coordinated development of new forms of digital-intelligence economy. By releasing the value of data elements and promoting the digital flow and allocation of production factors, digital transformation can not only enhance the innovation vitality and output level of cities but also promote the construction of an open, inclusive, and sustainable global innovation ecosystem [6].

2. Theoretical Analysis and Research Hypotheses

Urban digital transformation serves as a pivotal force driving high-quality regional economic development. The rapid development and widespread application of digital technologies such as big data, cloud computing, and artificial intelligence have transformed data into a crucial production factor in modern economic activities, profoundly influencing urban innovation and development. On the one hand, massive data provide rich materials for urban innovation. Leveraging digital technologies, cities can mine valuable information from big data, facilitating the discovery of new development opportunities and technological pathways. It promotes the conduct of regional innovation activities. On the other hand, data has permeated every aspect of urban development. Through digital transformation, cities can achieve industrial upgrading, infrastructure optimization, and public service enhancement. The multifaceted digitization, networking, and intellectualization significantly enhance operational and innovation efficiency. It can be argued that the development and application of digital technologies are reshaping urban innovation models, with both the quantity and quality of urban innovation exhibiting new characteristics and trends [7]. Digitalization uses digital technology to strengthen information flow and enhance inno-

vation management. Meanwhile, the active application of digitalization can positively promote value creation [8]. Digital transformation exerts a significant enabling effect on enhancing the quality of collaborative innovation. Digital technologies themselves offer new tools and channels for corporate innovation and R&D. These digital technologies assist innovative enterprises in mitigating risks and difficulties associated with high-quality innovation, thereby promoting the improvement in collaborative innovation quality. At the same time, digital products represented by artificial intelligence and blockchain have established efficient and convenient platforms for collaborative innovation. Relying on digital platforms, talent mobility and information sharing become smoother. A diversified knowledge structure is conducive to inspiring innovation and realizing cross-regional and cross-field collaborative innovation. It is found through empirical research that digital transformation has a significant promoting effect on innovation efficiency [9]. The deep co-creation brought about by digital transformation has injected new impetus into enhancing the quality of cooperation and innovation [10].

The development of digitalization not only changes the relationship network among organizations but also gives birth to the network externalities effect [11]. The deep integration of digital technology and the real economy has upended traditional business models and reshaped the global competitive environment. This intensified market competition has compelled innovative entities to strengthen their innovative consciousness and motivation, thereby seeking survival and growth through innovation. At the same time, in the digital economy era, cooperation and collaboration among cities have become increasingly intimate. It is necessary to foster mutually beneficial and win-win innovation ecosystems within and across industries. As an important innovation subject, enterprises, especially listed companies, often carry out cooperative innovation through huddling together and complementing each other's advantages [12]. In the new wave of technological revolution and industrial transformation, the pace of survival of the fittest has accelerated significantly. In this context, continuous high-quality innovation has become a key strategy for enterprises to maintain their advantages in global competition. Generative AI is reshaping the business models of digital enterprises, affecting value creation, customer interaction and so on [13]. It is thus evident that digital development is compelling enterprises, as innovative entities, to intensify their innovative efforts and undertake substantive innovation activities to enhance innovation performance [14]. Cross-regional collaborative innovation, as a crucial innovation mode, has revitalized in the digital economy era [15]. The wide application of digital technologies makes the connection between regions closer. The spatial and temporal barriers to collaborative innovation have been greatly weakened. Researchers studied the impact of digital transformation on corporate green innovation using Chinese manufacturing listed companies as their research subjects [16]. This reflects the positive role of digitalization in promoting the global sustainable development goals. Their empirical results indicate that digital transformation can significantly enhance green innovation levels, underscoring its positive role in promoting sustainable development. Based on the above analysis, this paper proposes the following hypothesis:

H1. *Digital transformation facilitates the improvement in cross-regional collaborative innovation quality.*

Collaborative innovation networks contain abundant resources such as knowledge, information, and capital. Under the global knowledge economy system, cities are important nodes in the innovation network. Elements of innovation can interact and integrate dynamically within the innovation network [17]. The network location of a city and the degree of embedding in its relationship with partners directly affect the efficiency of knowledge flow and the quality of innovation achievements and influences innovation behavior and performance. Relational embeddedness refers to the degree of cooperation, trust, and

closeness in relationships formed by innovation actors within collaborative networks based on shared aspirations. The relationships established between the city where the enterprise is located and the partner city can create unique social capital, influencing its innovation performance [18]. The relational embeddedness between cities not only constitutes the social capital basis for cross-regional activities but is also further strengthened in the process of digitalization, promoting the formation of a more open, dynamic, and efficient global innovation network. It is pointed out that digital transformation confronts numerous challenges, necessitating enhanced coordination and collaboration among stakeholders [19]. In the context of global digital transformation, stakeholders face multiple challenges such as technology integration and data governance [20]. These challenges urgently require enhancing internal coordination within the network to drive systemic change. Digital transformation accelerates the relational embeddedness between an enterprise located among cities and collaborating cities. So, it builds a closer connection, which helps enterprises to obtain network resources and improve innovation performance [21]. Firstly, as the degree of relational embeddedness deepens among cities, actors in the innovation network gain access to richer innovative elements such as knowledge, technology, and talent [22]. This enables inter-regional knowledge spillovers and technology transfers. Global digital platforms offer diverse interaction modes for innovation actors, combining online virtual interactions with offline face-to-face exchanges [23]. Digital platforms not only reduce the cost of searching for partners for innovation actors, but it also is conducive to the dissemination of tacit knowledge [24]. Firms can improve their innovation performance by adopting digital platforms [25]. Secondly, sustained and frequent interactions among cities enhance understanding and trust among innovation actors. Trust-based partnerships can reduce opportunistic risks in the collaboration process and stimulate the enthusiasm of all parties to advance innovation projects. Thirdly, relational embeddedness also presents enterprises with more innovation opportunities. The embeddedness of the city where the enterprise is in the cooperative network relationship is deep, and the advantages of market information and technical information can be obtained through network contact. Therefore, it is possible to grasp innovation opportunities [26].

Furthermore, research proposed an analytical framework for the integration of cross-regional innovation systems, which underscores the pivotal roles of knowledge bases, network connections, and institutional environments in driving innovation [27]. Digital transformation has accelerated the cross-regional dissemination of knowledge worldwide and has also broadened the scope and deepened the reach of innovation networks, optimizing the institutional environment for innovation [28]. It is point out that deploying digital platforms in smart specialization strategies enables data intelligence and collaborative innovation [29]. To sum up, driven by digital transformation, intercity relationship embeddedness brings about paths such as knowledge spillover, transaction cost reduction, and access to innovation opportunities. It can effectively improve the quality of cross-regional cooperation and innovation. Based on these insights, the following hypothesis is proposed in this paper:

H2. *The relational embeddedness of a collaborative network mediates the relationship between digital transformation and the quality of cross-regional collaborative innovation.*

The impact of enterprise digital transformation on the quality of cross-regional collaborative innovation may exhibit nonlinear characteristics. The implementation of open innovation entails a threshold effect, requiring enterprises to possess a certain level of digital foundation and absorptive capacity. From a global perspective, during the initial stages of digital transformation, the enhancement of digital technology application and digital capability can provide more opportunities and conveniences for cross-regional

collaborative innovation, which can promote the improvement in innovation quality [30]. The application of digital technologies breaks through spatial and temporal constraints, enabling cities where enterprises are located to access and integrate innovation resources dispersed across different regions more easily. As a technological driving force, digital transformation affects the flow of knowledge within enterprises, reduces transaction costs and improves the speed of decision-making response [31]. Real-time interactions and remote collaborations with partners facilitate the joint development of new products, technologies, and business models. Additionally, digital transformation enhances the data processing and analytical capabilities of innovation actors, enabling the full exploitation and utilization of big data. With an in-depth understanding of market demands and technological trends, digital transformation provides precise support for innovation activities. Furthermore, the development of digitalization promotes the optimization and reengineering of internal innovation processes, further improving operational efficiency and response speed. It provides stronger organizational guarantees for cross-regional collaborative innovation.

However, the excessively high level of digitization means that enterprises need to manage and coordinate more complex internal and external innovation networks. When the digitization level exceeds a certain threshold, issues such as increased network complexity, knowledge redundancy, and partner opportunism may negatively impact collaborative innovation [32]. Ultimately, the quality of innovation deteriorates. Differences between partners in terms of goals, interests and culture are likely to intensify. Communication and coordination costs increase and decision-making efficiency decreases, thus weakening the quality and efficiency of collaborative innovation. Moreover, in the digital era, innovation actors have access to vast amounts of data and information. The application of digital technologies enhances their abilities to screen, extract, and evaluate the value of information, leading to faster and more efficient updates in innovative knowledge, further promoting innovation quality. Based on the endogenous growth theory, the development of digital technology is conducive to the search, dissemination and processing of information and knowledge [33]. When the degree of digitalization is high, mutual dependence among collaborating cities deepens. On the one hand, this strengthens the trust foundation and collaboration motivation among cities. On the other hand, it also inversely drives the enhancement of intellectual property protection. With the continuous improvement in the digitalization level of high-tech enterprises worldwide, their performance in cross-regional cooperative innovation often shows phased characteristics. In the early stages of digitalization, technology enables the expansion of collaboration channels, optimizes resource allocation, and elevates innovation performance. Digital technologies such as cloud computing, big data, and artificial intelligence establish efficient and collaborative innovation platforms for high-tech enterprises, facilitating the flow and integration of cross-regional innovation factors. Simultaneously, digital transformation enhances enterprises' fast learning capabilities and innovation adaptability, enabling them to better seize market opportunities and respond to external environmental changes [34]. So, it promotes the emergence and transformation of innovative outcomes. However, once the level of digitalization exceeds the enterprises' management and response capabilities, the quality of collaborative innovation may suffer. Excessively high digitalization imposes higher demands on enterprises' organizational structures, management models, and talent pools. The digital divide and capability gap cannot be ignored. Differences in digital infrastructure, technological capabilities and talent reserves among different regions, industries and enterprises may also lead to the emergence of a digital divide, thus affecting the effect and equity of collaborative innovation [35]. Therefore, in research on the impact of digital transformation on the quality of cross-regional collaborative innovation, it is crucial to

balance digital transformation and internal–external resource integration, exploring the specific content of its threshold effect. Based on this, the following hypothesis is proposed:

H3. *Digital transformation has a nonlinear effect on promoting the quality of cross-regional cooperation and innovation. Namely, the higher the level of digitalization, the stronger its promotional effect up to a certain point.*

To sum up, this study builds a theoretical analysis framework for examining the impact of digital transformation on the quality of cross-regional collaborative innovation. Digital transformation exerts a positive influence on the quality of cross-regional collaborative innovation through both direct pathways and the mediating role of relational embeddedness. Meanwhile, the influence of digital transformation exhibits nonlinear characteristics, shown as a threshold effect. This framework helps to understand the evolution of innovation networks in the context of digitalization. It can also provide theoretical reference and practical enlightenment for governments and enterprises to formulate digital transformation strategies and optimize the governance of innovation ecosystem.

3. Research Methods and Data Sources

3.1. Research Design

This paper focuses on the core question of how digital transformation affects the quality of cross-regional collaborative innovation. In Section 2, we clarify the mechanisms underlying the impact of digital transformation on the quality of cross-regional collaborative innovation and accordingly propose research hypotheses. Recognizing that the cross-regional collaborative innovation network serves as a crucial lens for examining the quality of such innovation, social network analysis methods are adopted to describe the structural characteristics and dynamic changes in China's cross-regional collaborative innovation network prior to empirical research. Then, this study constructs a collaborative innovation network based on the quantity and quality of cross-regional collaborative innovation among Chinese cities. The analysis of the collaboration network is conducted from three aspects, including temporal evolution features, topological structural features, and spatial variation patterns, elucidating the inter-city cooperative innovation network, urban cooperative relations and spatial distribution characteristics. In terms of measuring the level of digital transformation, we draw on four dimensions including artificial intelligence, blockchain, cloud computing, and big data to characterize this level and further explore its facilitation and impact mechanisms on the quality of cross-regional collaborative innovation [36]. The research framework is shown in Figure 1. In the empirical research part, this paper uses the econometric model to test the impact of digital transformation on the quality of cross-regional cooperation innovation and conduct heterogeneity analysis. Within the nonlinear relationship, the application of digital technologies and their impact vary across different stages of digital transformation development. Differences in the digitalization level among various actors within the collaboration network also lead to varying degrees of improvement in the quality of collaborative innovation, manifesting as a threshold effect. Finally, Section 6 summarizes the research findings, offers relevant insights, and outlines future directions.

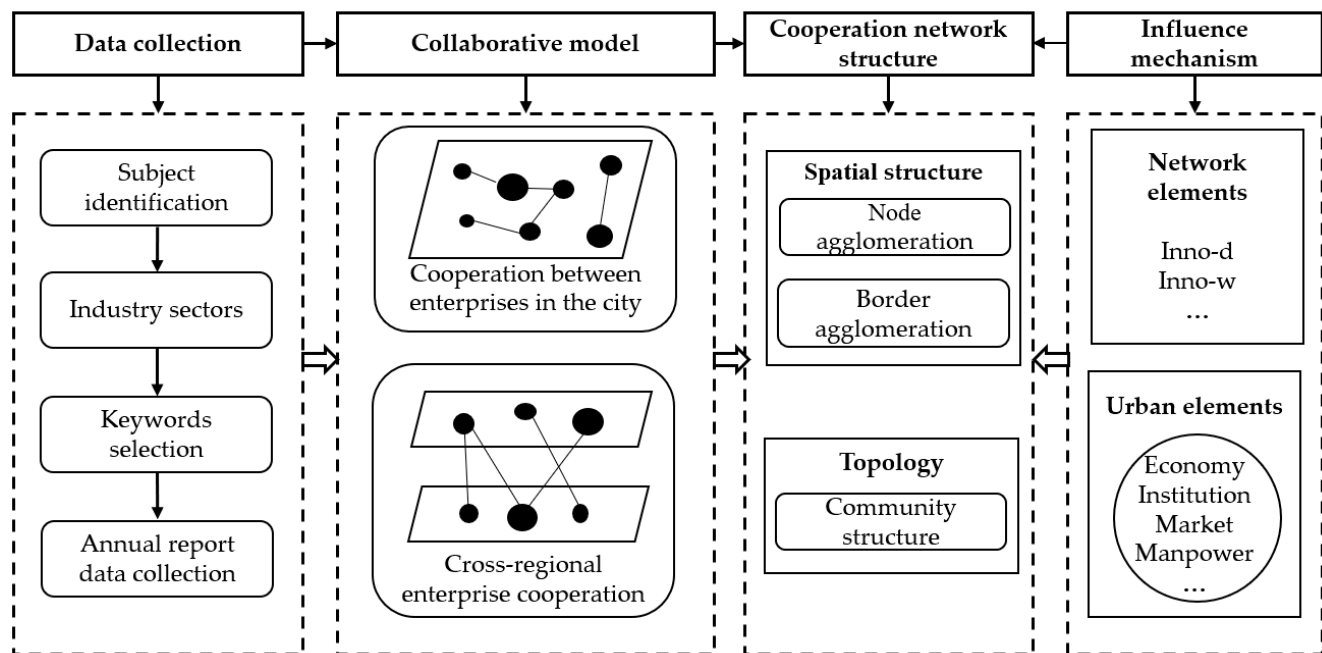


Figure 1. Research framework of cross-regional cooperative innovation network.

3.2. Sample and Data

This paper takes A-shared listed companies in China's Shanghai and Shenzhen stock exchanges as the research sample during the period from 2011 to 2021. Samples labeled as ST and *ST, as well as those with severe levels of missing data, are excluded. The primary data of listed companies are sourced from the China Stock Market Accounting Research (CSMAR) database and the Chinese Research Data Services Platform (CNRDS). Data on corporate digital transformation are derived from annual reports of listed companies. The raw data related to innovation originate from the China National Intellectual Property Administration (CNIPA) database. Additionally, the city-level data is obtained by matching the address of the listed company of the patent application subject and aggregating statistics. Data for other control variables are primarily sourced from the National Bureau of Statistics of China and China Statistical Yearbook, and logarithmic transformations are applied based on the final form of the variables.

3.3. Model Setting

To test the research hypothesis proposed in this paper, the following basic regression model is set up as follows:

$$Inno_{it} = \alpha_0 + \alpha_1 Dige_{it} + \alpha Control_{it} + \mu_i + \sigma_t + \varepsilon_{it} \quad (1)$$

Utilizing patent application information from listed companies on the Shanghai and Shenzhen stock exchanges, collaborative patents with listed companies as the main innovators are selected. Gephi 9.7 is used to construct a cross-regional collaborative innovation network and weights the network based on the number of patent citations. In this study, the explained variable ($Inno_{it}$) represents the quantity and quality of cross-regional collaborative innovation. We draw on the methodology, which uses the quantity of inter-city patent collaborations to calculate the quantity of cross-regional collaborative innovation [37]. However, recognizing that similar patents do not necessarily enhance corporate productivity [38], we also employ the citation frequency of collaborative patents between cities to gauge the quality of cross-regional collaborative innovation. The core explanatory variable ($Dige_{it}$) is digital transformation. Following the systematic review of the relationship be-

tween digital transformation and innovation, we conceptualize digital transformation as “an ongoing socio-structural change that leverages digital technologies to create new value toward sustained competitive advantage” [39]. We argue that our textual analysis approach, based on annual report keyword frequency, is inherently consistent with this definition. On the one hand, the frequency of digital-related keywords captures firms’ strategic intention to leverage digital technologies, as annual reports serve as authoritative disclosures of managerial attention and resource allocation priorities. On the other hand, the annual variation in keyword frequency reflects the ongoing evolution of firms’ digital discourse, illustrating their continuous adaptation to technological changes and dynamic strategic responses. Building on this foundation, and according to the practice, we collected annual report data of all A-share listed companies in Shanghai and Shenzhen using Python3.10 [40]. We constructed a structured taxonomy of enterprise digital transformation and conducted keyword frequency retrieval, matching, and statistical analysis based on 76 digitalization-related terms like intelligent robot, data mining, cloud computing, blockchain, mobile internet and so on. Finally, we matched firms with their corresponding cities based on listed company information and aggregated the digital transformation levels to the city level, constructing a proxy variable for the degree of digital transformation. $Control_{it}$ represents control variables, which include indicators such as urban population density, regional gross domestic product, the proportion of secondary and tertiary industries, the proportion of government expenditure, and the number of listed companies in the city. This study takes logarithms of the control variables to eliminate data dimensions and increase the comparability of indicator coefficients. The subscripts i and t represent cities and years, respectively. μ_i represents city fixed effects and σ_t represents time fixed effects. The ε_{it} is the random error term.

The following model is then constructed to examine the mediating effect:

$$Rela_{it} = \beta_0 + \beta_1 Dige_{it} + \beta Control_{it} + \mu_i + \sigma_t + \varepsilon_{it} \quad (2)$$

$$Inno_{it} = \gamma_0 + \gamma_1 Dige_{it} + \gamma_2 Rela_{it} + \gamma Control_{it} + \mu_i + \sigma_t + \varepsilon_{it} \quad (3)$$

The intermediate variable ($Rela_{it}$) is relational embeddedness. It is measured by the strength of the relationship between the city and other organizations in the cross-regional cooperation network. We adopt the intermediary centrality (a network index) in the cooperative innovation network to measure the indicator [41].

Furthermore, the effect of the degree of digital transformation on the quality of collaborative innovation is influenced by the level of digital technology development. At the level of digital technology innovation, there is a nonlinear relationship between them. Therefore, this study adopts the panel threshold model to examine this relationship, and the panel threshold model is set as follows:

$$Inno_{it} = \alpha + \beta_1 Dige_{it}(DI_{it} \leq \rho) + \beta_2 Dige_{it}(DI_{it} > \rho) + \beta Control_{it} + \varepsilon_{it} \quad (4)$$

In the formula, DI_{it} represents the threshold variable, that is, the number of digital patent applications. $I(DI_{it})$ is the indicator function. When DI_{it} meets the conditions, the value is 1. Otherwise, the value is 0. β_1 and β_2 are the estimated coefficients under the corresponding thresholds. ρ represents the threshold to be estimated. β represents the estimated coefficients of each control variable. The specific variables are explained in Table 1.

Table 1. Main variable definitions and descriptions.

Variable Attribution	Variable Name	Variable Description
explained variable	Inno-d	The degree of the cooperative innovation network
	Inno-w	The weighted degree of the cooperative innovation network
explanatory variable	Dige	The degree of digital transformation
intermediate variable	Rela	The relational embeddedness of the cooperative innovation network
threshold variable	DI	The number of digital patent applications
Control variable	density	Logarithmic value of population density (10,000 people/km ²)
	gdp	Value of gross regional product (billion Yuan)
	p2	The proportion of secondary industry (%)
	p3	The proportion of tertiary industry (%)
	cost	The ratio of government spending to GDP (%)
	num1	Logarithmic value of the number of listed companies

4. Cross-Regional Cooperation Innovation Network Analysis

4.1. Temporal Evolution Characteristics of Urban Cooperative Innovation Network

The innovation cooperation network between cities in the world shows a significant trend of expansion and deepening. This phenomenon is particularly evident in many economies, especially in emerging innovation systems. Innovation activities are undergoing a paradigm transition from localized agglomeration to cross-regional network collaboration, and dynamic innovation networks promote the reconstruction of city-centered innovation within the network space [42]. In the case of China, the scale of inter-city cooperation and innovation networks in China has expanded rapidly from 2011 to 2021. Table 2 describes the basic information of network changes during the study period. During the research period, the number of network nodes (cities) increased from 130 to 278, while the flow of patent cooperation relationships soared from 252 to 1660. This indicates that more and more cities are participating in the patent cooperation network, and both the network scale and the quantity of collaborative ties exhibit an upward trend. Notably, the network density of patent cooperation among Chinese cities has increased from 0.027 to 0.033, showing a heightened regionalization trend within the Chinese urban patent cooperation network. Within this network, the intensity of collaboration among cities has shown a steady increase. The Chinese inter-city cooperative innovation network has experienced rapid structural growth during this period, and the relevant data can provide a useful reference for understanding the evolution of the global urban innovation network. Patents are no longer just working with a specific city but increasingly connecting with cities. The average degree of the cooperation and innovation network, reflecting the mean number of connections each city has with other cities, increased from 1.938 in 2011 to 5.971 in 2021. This significant upsurge demonstrates the enhanced interconnectedness among cities in patent collaborations. Concurrently, as more cities join the patent cooperation network, the cohesion of the network structure gradually improves. The average weighted degree, representing the quantity of patent cooperative innovations between a city and its connected partners, increased from 8.515 in 2011 to 91.435 in 2021. This signifies that an increasing number of cities are opting to transcend administrative boundaries in search of high-quality patent resources. In summary, the Chinese urban cooperation and innovation network has not only witnessed a rapid intensification of inter-city collaboration but also a diversification in the choice of collaborative partners. Patent cooperation between regions and cities is becoming increasingly intertwined. This change not only reflects the spatial reconstruction of innovation resources within a single country but also is consistent with the international trend of the development of a multicenter global innovation network. It

provides an empirical reference for understanding the structural dynamics of cross-regional innovation cooperation in the context of the digital economy.

Table 2. Statistics on complexity characteristics of city patent cooperation networks in China from 2011 to 2021.

Year	Network Scale			Small-Worldness		Degree Centrality	Intensity Centrality
	Node	Edge	Graph Density	Average Path Length	Average Clustering Coefficient	Average Degree	Weighted Degree
2011	130	252	0.027	3.165	0.277	1.938	8.515
2012	182	592	0.029	2.685	0.398	3.253	31.055
2013	199	661	0.026	2.657	0.512	3.322	45.960
2014	208	723	0.026	2.646	0.482	3.476	51.308
2015	210	810	0.029	2.550	0.491	3.857	66.567
2016	211	792	0.028	2.641	0.475	3.754	61.351
2017	226	936	0.029	2.635	0.499	4.142	71.248
2018	237	1069	0.030	2.545	0.493	4.511	79.287
2019	253	1274	0.031	2.607	0.519	5.036	81.134
2020	267	1484	0.032	2.554	0.491	5.558	85.528
2021	278	1660	0.033	2.584	0.473	5.971	91.435

4.2. Topological Structure Characteristics of Urban Cooperative Innovation Network

In this research, Gephi9.7 is used to comprehensively describe China's inter-city cooperative innovation network in two time periods of 2011 and 2021. Overall, the degree of the network module decreases year by year, from 0.605 in 2011 to 0.396 in 2021. The community structure is increasingly fragmented. As can be seen from the community division of the cooperative network, the connections within the community become sparse. During the evolution of the inter-city cooperative innovation network, cities actively seek or attract partners. The average network path length in 2011 and 2021 is 3.165 and 2.584 respectively. The short average path length of the cooperative innovation network is consistent with the characteristics of the small-world network.

As shown in Figure 2a, China's urban patent cooperation network took shape initially in 2011, with a distribution pattern centered on a few core cities. In 2011, the collaborative innovation network formed 11 major communities, including Beijing–Dongying, Shenzhen, Guangzhou–Shantou, Shanghai–Hangzhou–Nanjing, Zhuhai–Zhongshan, Tianjin, Wuhan, and Xiamen. The collaborative innovation network primarily focused on patent cooperation among geographically adjacent cities, with the strongest ties observed between Guangzhou–Shantou, Beijing–Dongying, and Beijing–Tianjin. These representative cities with close collaboration are geographically proximate. It is shown that geographical proximity can help reduce cooperation costs, enhance collaboration efficiency, and facilitate the sharing and optimal allocation of innovation resources. Meanwhile, during this period, innovation activities within the collaboration network were primarily concentrated in first-tier cities and their adjacent cities within their radiation range. Among them, Beijing, Guangzhou, Shantou, Shanghai, and Shenzhen emerged as the leading cities for patent cooperation. Beijing, with its vast patent portfolio and extensive collaboration scope, stood as the absolute core of the urban patent cooperation network. Major cities like Shanghai and Guangzhou leveraged their innate innovation capabilities and close cooperative relationship with the surrounding cities, promoting the nascent development of the collaboration network. The formation of community structures within the 2011 collaboration network was primarily influenced by various factors such as geographical location, economic development level,

industrial structure, and policy guidance. Overall, the number of participating cities was relatively small, leading to modest-sized communities. There were certain limitations in patent collaboration between cities. Core cities played a pivotal role in the urban patent cooperation network, not only possessing robust innovation capabilities but also effectively establishing close collaborative ties with neighboring cities.

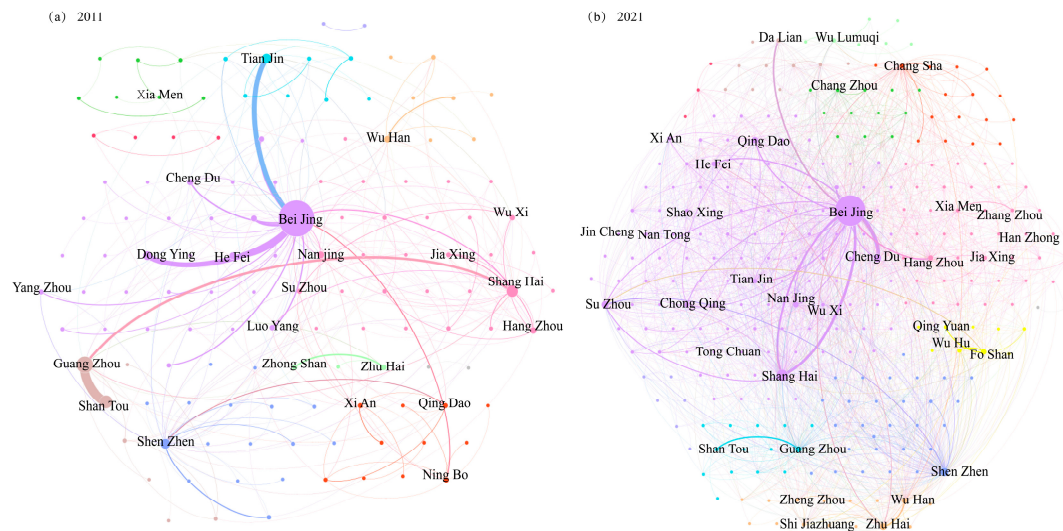


Figure 2. Patent cooperation network community structure among Chinese cities. (a) Chinese patent cooperation network community structure in 2011. (b) Chinese patent cooperation network community structure in 2021.

Different colors in Figure 2 represent different communities. The size of the circle represents the weighted centrality. The larger the circle, the higher the weighted centrality and vice versa. The thickness of the edge represents the amount of patent cooperation between cities. The thicker the edge, the greater the number of patent collaborations and vice versa.

With the popularization of digital technology, there was an improvement in cross-regional infrastructure and the acceleration of the global flow of innovative resources. The collaborative innovation network between cities is gradually evolving in the direction of complexity and polycentralization. Patent cooperation between cities is becoming more and more frequent. A complex cooperative innovation network structure has been further formed. As shown in Figure 2b, the topology of China's urban patent cooperation network in 2021 has undergone great changes compared with 2011. The community structure has gradually differentiated and reorganized. The overall community size has become larger. The major cooperative societies have gradually differentiated and restructured. The cooperation associations mainly include 12 associations, such as Beijing–Shanghai–Chengdu, Shenzhen, Xiamen–Hangzhou, Foshan–Qingyuan, Changsha, Zhuhai–Wuhan, etc. The new associations are mainly concentrated in first-tier and new first-tier cities. Based on their regional innovation resources and environment, as well as their economic development needs, these cities play an important role in the cooperative innovation network. Compared with the initial stage, the cooperation network in 2021 has formed a new cooperation pattern, which is not only reflected in the increase in the number of societies but also in the expansion of the scale of societies. It is worth noting that with the continuous progress of information technology and transportation networks, the restriction of geographical distance on cooperation has gradually weakened. Cross-regional cooperation is becoming more frequent. Core cities assume the function of bridging different communities in the network, reflecting their central role in regional and even global innovation flows. With

their strong scientific and technological strength and innovation ability, Beijing, Shanghai, Shenzhen, and other cities became the core cities of the urban patent cooperation network during this period. Beijing is becoming a bridge and bond connecting various communities in the network. This core position not only reflects Beijing's leading position in scientific and technological innovation but also reflects its important role in regional economic development. In summary, the evolution of the topology of cooperative innovation networks reveals the trend of innovation activities transforming from geographical agglomeration to networking and cross-regional linkage. At the same time, it also reflects the process of accelerating the sharing and reorganization of knowledge, technology, data, and other innovation elements on a global scale. This change is consistent with the direction of multi-center and high-efficiency development of the global innovation system, which provides an important basis for understanding the spatial pattern and evolution mechanism of urban collaborative innovation in the context of digital transformation.

4.3. Spatial Characteristics and Evolution Law of Urban Cooperative Innovation Network

Based on the quality of patent cooperation among Chinese cities, ArcGIS 10.2 is used to describe the cooperative innovation network of Chinese cities (Figure 3). Overall, the cooperative innovation network of Chinese cities presents a significant rhomboid spatial structure. This quadrilateral structure constitutes the basic organizational form of the network and reflects the general spatial pattern of regional coordination and core-periphery structure interaction to a certain extent. As shown in Figure 3a, in 2011, Beijing, Shanghai and Tianjin were the major cities in China for cooperative innovation. Based on the Beijing–Tianjin–Hebei city cluster, Yangtze River Delta city cluster, Pearl River Delta city cluster and Chengdu–Chongqing city cluster, the basic diamond shape framework of China's urban cooperative innovation network is constructed. However, the spatial characteristics are shown significantly as east being dense west being sparse. Among them, the Yangtze River Delta city cluster, the Pearl River Delta city cluster and the Beijing–Tianjin–Hebei city cluster have close internal cooperation. There is less internal cooperation in the Chengdu–Chongqing city agglomeration. Beijing shows the absolute core position of innovation cooperation and is the main cooperation object of first-tier cities in the west and east. With the promotion of national and regional innovation policies, the improvement in scientific and technological infrastructure, and the enhancement of digital linkages, the innovation cooperation capacity of western China has been significantly improved. As shown in Figure 3b, Beijing, Shanghai, Chengdu, and Shenzhen were the four cities with the highest quality of cooperative innovation in China in 2021. The western region, dominated by the Chengdu–Chongqing city cluster, has significantly strengthened its capacity for innovation cooperation. Among them, the quality of innovation cooperation between Chengdu and Beijing and the eastern coastal cities is the most significant. This strengthened the quadrilateral structure of the construction of China's innovation highland and showed a strong peripheral radiation effect. This change not only strengthens the stability and integrity of the rhombohedral quadrilateral structure but also drives the radiation and diffusion of innovation elements to the surrounding areas, reflecting the spatial trend of polycentric and networked development. From a global perspective, this innovation network evolution path is driven by a few core cities, gradually extending inland, and forming a multi-polar linkage. This is similar to the spatial distribution in the construction process of regional innovation system in many economies. The cooperative innovation network of Chinese cities shows the characteristics of structural transformation from dense in the east and sparse in the west to a four-pole linkage. This reflects the effectiveness of regional development strategies in China and provides an empirical reference for understanding

how late-developing regions integrate into the global innovation network through policy guidance and facility construction.

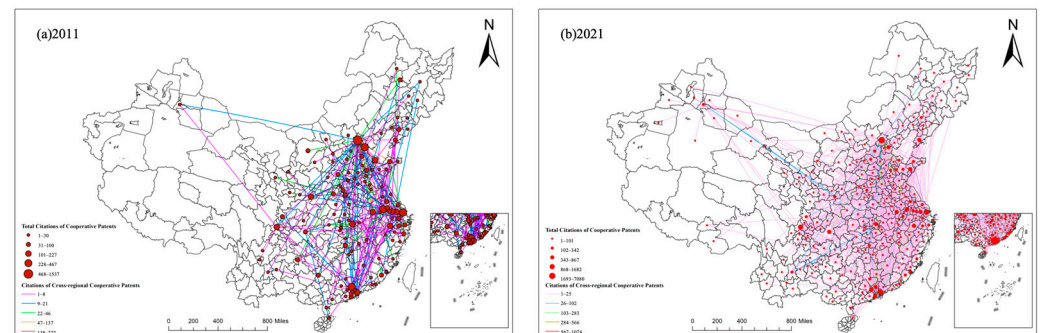


Figure 3. Citations of cross-regional cooperative patents in China. (a) Citations of cross-regional cooperative patents in China in 2011. (b) Citations of cross-regional cooperative patents in China in 2021.

5. Empirical Results and Heterogeneity Analysis

5.1. Empirical Analysis

5.1.1. Regression Results

Columns (1) and (2) in Table 3 report estimates of the quality and quantity of cross-regional collaborative innovation from digital transformation. The results reveal the profound impact of urban digital transformation on cross-regional cooperative innovation. After controlling for year and region fixed effects and other urban characteristic variables, the regression coefficients of the digital transformation index are significantly positive at the level of 1%. This result not only provides strong empirical support for Hypothesis 1 but also reveals the dual role of digitalization in reshaping the innovation paradigm. From the perspective of effect size, the influence coefficient of digital transformation on the quantity of cooperation innovation is 0.079, while the influence coefficient of digital transformation on the quality of cooperation innovation is as high as 2.697. This significant difference has profound economic implications. Digital transformation is not only an incremental technology but also an enabling effect. Specifically, for every 1% increase in the level of digital transformation, the number of cross-regional cooperative patents produced by enterprises in a city will increase by about 0.079%, and the citation volume of these patents (as a proxy variable of quality) will significantly increase by about 2.697%. The order of magnitude of the latter coefficient is much larger than that of the former. It shows that the core value of digital technology is not simply to increase the frequency of innovation activities but to profoundly change the underlying logic of knowledge production. The internal mechanism of this phenomenon lies in the following aspects. Under the traditional innovation model, geographical distance and administrative boundaries are natural barriers to knowledge spillovers. The penetration of digital technology, firstly, reduces the cost of trial and error so that enterprises can use big data analysis to accurately capture market demand and technology gaps. Therefore, innovation resources can be shifted from inefficient repetitive R&D to high-value breakthrough exploration. Secondly, by breaking down organizational barriers, digital platforms build innovation platforms across time and space. It also enables the know-how to be coded and flow rapidly. It promotes in-depth knowledge integration among innovation subjects in different cities. The platform and intelligent features not only increase the number of cooperative innovation achievements, but, more importantly, the versatility, frontier and practicality of its technical solutions are also greatly enhanced. This is directly reflected in the doubling of the patent citation volume. Therefore, digital transformation breaks the barriers of internal and external coordination and communica-

tion between cities and speeds up the knowledge interaction and collaboration between each other.

Table 3. Empirical results of digital transformation level on the quality of cross-regional cooperation innovation.

	(1) Inno-d	(2) Inno-w	(3) Rela	(4) Inno-w
Dige	0.079 *** (24.55)	2.697 *** (8.49)	1.978 *** (10.93)	0.852 *** (3.08)
density	−0.171 (−0.69)	−50.350 ** (−2.06)	6.267 (0.45)	−56.195 *** (−2.71)
gdp	3.945 *** (10.60)	261.522 *** (7.11)	106.069 *** (5.06)	162.606 *** (5.18)
p2	−6.632 *** (−4.37)	292.405 * (1.95)	−398.053 *** (−4.66)	663.615 *** (5.20)
p3	−5.115 *** (−3.42)	−72.862 (−0.49)	−342.236 *** (−4.06)	246.296 * (1.96)
cost	1.186 * (1.84)	188.437 *** (2.95)	31.292 (0.86)	159.256 *** (2.94)
num1	3.072 *** (11.39)	6.223 (0.23)	82.507 *** (5.43)	−70.720 *** (−3.11)
Rela				0.933 *** (28.91)
_cons	11.100 (0.95)	−2931.681 ** (−2.54)	1792.399 *** (2.72)	−4603.208 *** (−4.69)
N	2381	2381	2381	2381
R ²	0.658	0.146	0.280	0.387

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The results of columns (3) and (4) in Table 3 further reveal the internal mechanism of how digital transformation affects innovation, that is, by enhancing the relational embeddedness between cities. The regression results after adding the intermediary variable of relational embeddedness show that relational embeddedness plays a mediating role in the relationship between digital transformation and the quality of cross-regional cooperation and innovation. Hypothesis 2 is supported. Column (3) shows that the influence coefficient of digital transformation on relational embeddedness is significantly positive at the level of 1%. It shows that the improvement in digital infrastructure and the application of digital technology have effectively reduced the communication costs and risks of inter-city enterprise collaboration. Supported by digital twins, collaborative platforms and blockchain trust mechanisms, node cities in the cooperative network can establish more frequent and transparent interactions. Thus, a higher degree of mutual trust, mutual benefit and long-term commitment can be fostered, which is the core meaning of relationship embeddedness. The results in column (4) complete the closure of the transmission chain. After controlling for the direct effect of digital transformation, the influence coefficient of relational embeddedness on cooperation innovation quality is also significantly positive at the level of 1%, which confirms that relational embeddedness plays a significant mediating role. Digital transformation builds the hard connectivity of the cooperative network, while relational embeddedness activates the soft connectivity of the network. From the perspective of knowledge governance, high-intensity relational embeddedness means that the two partners go beyond the simple market transaction relationship and form a problem-solving partnership. This close relationship facilitates the transfer of complex tacit knowledge. High-quality innovations often rely on inexpressible technical know-how and experience, and only in an environment of high trust and close interaction are firms willing

to share this kind of core knowledge, thus creating patents that are more disruptive and highly cited. From the perspective of resource allocation, close relational embeddedness builds an efficient innovation community. Based on mutual trust, innovation subjects can carry out complementary allocation of innovation resources more quickly. Digital tools are responsible for the efficient matching of resources, while relational embeddedness is responsible for ensuring the quality of deep collaboration after matching. Ultimately, both point to the steady improvement in the quality of intellectual property creation.

To sum up, this part of the empirical research verifies the direct driving effect of digital transformation on cross-regional innovation. Through the analysis of mediating effects, the black box in which digital transformation affects innovation quality is opened. The enabling effect of digital transformation is reflected in the quantitative expansion and qualitative transition of cooperative innovation. The intermediary path of relational embeddedness shows the transition from technology empowerment to network mutual trust.

In this study, there may be a bidirectional causal relationship between digital transformation and cross-regional cooperative innovation networks. On the one hand, the improvement in the digitalization level may promote cooperative innovation among enterprises. On the other hand, the increased activity of the innovation network may also reverse-promote regional digital construction. In addition, there may be omitted variables (such as institutional environment and technological foundation) that affect both digital transformation and the innovation network structure, resulting in estimation bias. Therefore, it is necessary to use the instrumental variable method to alleviate the endogeneity problem. This study selects Digital_Attention as the instrumental variable. The index of digital attention is derived by analyzing government reports of various provinces and prefecture-level cities in China, sorting out the relevant digital texts and their word segmentation results from aspects such as digital technology and digital application [43]. Digital attention reflects the intensity of attention to digital issues, which will affect the process of regional digital transformation [44]. The government work reports published by prefecture-level cities are programmatic policy texts, which fit the relevant influence of China's unique state-led regional policies. The government's policy orientation and focus are important external driving forces for enterprises' digital transformation, but the government's digital attention itself does not directly participate in the process of cross-regional cooperative innovation. Specifically, on the one hand, in-depth mining and analysis of the government work report can effectively measure the government's investment and attention in the development of the digital economy, which is related to the degree of digital transformation. It satisfies the relevance assumption of the instrumental variable. On the other hand, the government's digital attention is a kind of policy signal, mainly from the macro strategic layout, rather than driven by the existing cooperative innovation achievements of enterprises. It is difficult for the instrumental variable to directly intervene in the specific details of cross-regional R&D cooperation among innovators. Compared with the micro innovation behavior of individual enterprises, it has strong exogeneity. The exogeneity requirement of instrumental variables is satisfied.

Firstly, in the endogeneity test of digital transformation on the quantity of cooperative innovation (with Inno-d as the proxy variable), the K-P LM statistic in Table 4 is significant ($p = 0.000$). The K-P Wald F value is 18.630, which is higher than the critical value of 16.38 for Stock–Yogo at the 10% level. It shows that there is no weak instrumental variable problem, namely, instrumental variables are valid. In column (1) in Table 4 with Dige as the dependent variable, the coefficient of Digital_Attention is 4652.0555, significant at the level of 1%, indicating that digital attention significantly promotes regional digital transformation. The overall R-squared value is 0.7380, indicating that digitalization has a strong explanatory power for the number of innovations. To enhance the robustness of

the conclusion, Table 5 further replaces the explained variable with cooperative innovation quality (with Inno-w as the proxy variable). Different from the degree in cooperative innovation networks, the weighted degree reflects the intensity of cooperation and can better describe the quality characteristics of innovation. If digital transformation still has a significant impact on weighted degree indicators, it indicates that digitalization not only expands the scope of cooperation but also improves the depth of cooperation. Therefore, it is necessary to redo the instrumental variable estimation under this indicator. Similarly, the K-P LM test is significant, and the K-P Wald F-value is greater than the critical value. It shows that instrumental variables still meet the identification conditions and that there is no weak instrumental variable problem. In column (1) in Table 5, the results are consistent with the previous ones, and digital attention significantly positively affects the level of digital transformation. It shows that instrumental variables are stable and effective. From the perspective of control variables, population density, GDP, government expenditure and the number of listed companies all promote digital development, with consistent results. In column (2) in Table 5 with Inno-w (weighting degree of cooperative innovation network) as the dependent variable, the Dige coefficient is 4.5242, which is significant at the 5% level. It shows that digital transformation significantly enhances the cooperation quality of cooperative innovation. This shows that digitalization not only increases the number of connections between innovation subjects but also strengthens the quality of cooperative relationships. In general, the two sets of results consistently show that digital transformation significantly promotes the formation and deepening of cooperative innovation networks, and the conclusions are robust and reliable after instrumental variable processing.

Table 4. 2SLS regression results of explained variable (Inno-d).

	(1) Dige	(2) Inno-d
Digital_Attention	4652.0555 *** (4.3163)	
Dige		0.0881 *** (3.6170)
Control	YES	YES
Time Fixed	YES	YES
City Fixed	YES	YES
N	1776	1776
F	18.3355	78.2014
Kleibergen–Paap rk LM	18.672	18.672
	[0.000]	[0.000]
Kleibergen–Paap rk Wald F	18.630	18.630
	{16.38}	{16.38}
R ²	0.4144	0.7380

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. [] represents the p -value of the statistic. The values within {} represent the critical values of the Stock–Yogo test at the 10% level.

Table 5. 2SLS regression results of explained variable (Inno-w).

	(1) Dige	(2) Inno-w
Digital_Attention	4652.0555 *** (4.3163)	
Dige		4.5242 ** (2.0424)

Table 5. Cont.

	(1) Dige	(2) Inno-w
Control	YES	YES
Time Fixed	YES	YES
City Fixed	YES	YES
N	1776	1776
F	18.3355	17.4710
Kleibergen–Paap rk LM	18.672	18.672
	[0.000]	[0.000]
Kleibergen–Paap rk Wald F	18.630	18.630
	{16.38}	{16.38}
R ²	0.4144	0.3792

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. [] represents the p -value of the statistic. The values within {} represent the critical values of the Stock–Yogo test at the 10% level.

5.1.2. Threshold Effect

At the same time, when the digital innovation represented by the number of digital patent applications is at different levels, the promotion effect of digital transformation on cross-regional cooperative innovation is different. In order to examine the nonlinear relationship between the two, the panel threshold model is adopted below to reveal whether the impact of the development level of digital transformation on cross-regional cooperative innovation is constrained by the number of digital patent applications. Table 6 reports the results of examining the threshold characteristics of the number of digital patent applications. First, the threshold effect is tested. Bootstrapping was used for repeated sampling 300 times, and a single threshold passed the significance test at 1% level. The double threshold failed the significance test. This suggests that the impact of digital transformation on the quality of cross-regional cooperation innovation has a threshold effect on the improvement in digital patent applications. Hypothesis 3 is verified.

Table 6. Test results of threshold model.

Threshold Test	F	10%	5%	1%
Single threshold	48.57 ***	8.075	10.823	45.875
Dual threshold	−7.91	22.065	28.093	46.051

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Furthermore, the formula is set as single-threshold, and threshold regression is performed on panel data. The estimated coefficients are shown in Table 7 below. The threshold regression results show that when the number of digital patent applications is lower than the first threshold value 866, the estimated coefficient of digital transformation is 2.559 and is significant at the 1% level. It shows that digital transformation can still promote the improvement in innovation quality of cross-regional cooperation even when the level of digital innovation is low. This may be because the process optimization and efficiency improvements brought about by digital transformation have a positive effect on collaborative innovation. On the one hand, based on the basic effect of digital transformation, the process of digital transformation involves the digital transformation of the business process, product design and service of the enterprise, which is an innovative subject. These fundamental changes can improve operational efficiency and responsiveness within organizations, even at low levels of digital innovation [45]. At the same time, the technology spillover effect brought by digital transformation makes it so that the new technology and new method introduced by digital transformation may still produce a technology spillover effect even

in the case of a small number of digital patents. This brings new ideas and methods for collaborative innovation. This also promotes the improvement in the quality of innovation. Digital transformation is one of the core drivers of organizational change, and organizations are at different stages of their transformation process with different levels of expertise in sustainability transformation [46]. When the number of digital patent applications exceeds the threshold (866), the estimated coefficient of the digital transformation level increases to 6.075 and is significant at the 1% level. This means that in the more active stage of digital innovation, the role of digital transformation in promoting the quality of cross-regional cooperative innovation is significantly enhanced. A higher level of digital innovation tends to reflect a more active atmosphere for technological R&D, a richer reserve of technological solutions, and a more mature knowledge sharing mechanism. Together, these factors strengthen the role of digital transformation in promoting deep collaboration across regions and stimulating high-quality innovation outcomes. In addition, the accumulation of digital technology has also enhanced the trust and synergy efficiency among nodes in the innovation network and promoted closer and more efficient cross-regional innovation cooperation. This finding echoes the view of the digital capability accumulation effect and innovation network synergy enhancement in global innovation research. This shows that the level of digital innovation is not only the basic condition for digital transformation to play a role but also the key regulating factor for its enabling effect to achieve high-quality collaborative innovation. The results have reference significance for economies in different innovation stages to formulate differentiated policies for the integration of digitalization and innovation.

Table 7. Estimated results of threshold regression model.

Threshold Variable	Coefficient	T Value
Dige ($DI \leq 866$)	2.559 ***	8.75
Dige ($DI > 866$)	6.075 ***	10.33
Control	YES	
R ²	0.688	
N	2381	

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.2. Heterogeneity Analysis

Globally, there are significant differences between different regions in terms of digital infrastructure, technology accumulation and innovation ecology. These differences have a profound impact on the enabling effect of digital transformation on the quality of cross-regional cooperative innovation. Although knowledge exchange exists between regions, each region utilizes the capabilities of other regions in different ways, and the level of knowledge spillover is also different [47]. Considering the significant unbalanced characteristics of various regions in China in terms of economic development level, institutional environment, factor endowment and administrative level, the enabling effect of digital transformation may show heterogeneity due to the location conditions and administrative status of cities. Therefore, this paper conducts grouping tests from the dimensions of geographical location and administrative level respectively. Firstly, this study conducts grouped regression analysis according to the geographical division of eastern, central, and western China to investigate the spatial boundary of the impact of digital transformation [48]. Secondly, according to the urban administrative level, the samples are divided into provincial capital cities (including sub-provincial cities) and non-provincial capital cities so as to explore the differentiated performance of high-level cities under the allocation of administrative resources [49]. In this way, we can reveal the heterogeneity of city size and hierarchy in the process of digital transformation. It should be noted that the

heterogeneity analysis in this part aims to reveal the coefficient differences in different sub-samples through grouped regression. In this way, we can describe the stylized characteristics of the digital transformation effect among different city types rather than using the interaction term test for strict statistical inference. Therefore, the following interpretation of the differences in coefficients between groups mainly focuses on the comparison in the economic sense rather than the significance discrimination in the strict statistical sense.

5.2.1. Regional Heterogeneity

Dividing China into eastern, central, and western regions, empirical analysis reveals that the development of digital transformation exerts notable heterogeneous effects on enhancing the quality of cross-regional collaborative innovation. Specifically, the regression coefficient for the eastern region is 2.869, it is 1.219 for the central region, and it is 8.501 for the western region, all significant at the 1% level.

The eastern region, as a leading area in economic and digital development, has a relatively complete information infrastructure, active innovation entities and a mature cooperation network. Its innovation actors possess more advanced technological equipment and sophisticated information systems, enabling them to access external innovation resources more conveniently and achieve cross-regional collaborative innovation. Digital transformation in this region is more manifested as efficiency improvements and network deepening of existing innovation systems, and its promoting effect is relatively stable and significant. The central region is in a stage of rapid development and transformation, and its digitalization level is gradually improving. During the digital transformation process, enterprises in the central region, as key innovation actors, actively seek cooperation with those in the eastern and western regions. Enterprises in this region are actively accessing a broader innovation network through digital means and introducing and absorbing external technologies and knowledge. Digital transformation plays a key role in promoting cross-regional collaboration and accelerating the diffusion of technology. It is worth noting that the regression coefficient of the western region is high. It indicates that digital transformation has the most significant impact on the quality of cooperative innovation in the region. This may be due to the fact that the original innovation foundation in the western region is relatively weak, and the reduction in network access, information accessibility and cooperation cost brought by digitalization has a more obvious marginal improvement effect. With the support of the national and regional coordinated development strategy and policy, the western region can link the innovation resources of the eastern and central regions more efficiently through digital leverage, thus realize a leapfrog improvement in innovation capacity. This finding is consistent with the trend of accelerated integration into global innovation networks through digital technologies in many late-developing regions around the world. It highlights the potential role of digitalization in promoting the reallocation and equitable development of innovation resources among regions.

5.2.2. Urban Heterogeneity

Here, the sample cities are divided into two groups for testing: central cities (including provincial capitals and sub-provincial and above cities) and “non-central cities”. The grouped estimates are reported in columns (4) and (5) of Table 8. Comparing the results, it can be found that the digital transformation indicators show a significant difference between central cities and non-central cities.

In the central city group, the estimated coefficient of digital transformation failed the significance test. This might be due to the fact that the central cities themselves already have relatively complete innovation infrastructure, rich cooperation channels and policy resources. The marginal improvement effect brought about by digital transformation is

relatively limited, and its innovation quality is more influenced by traditional elements such as institution, talents, and capital. At the same time, combined with the above analysis of cooperative innovation networks, most of the central cities are especially first-tier and new first-tier cities, which tend to occupy a dominant position in the regional network and have more abundant cooperative innovation resources, such as policy support and talent gathering. By contrast, in the non-central city group, the estimated coefficient of the digital transformation indicator is significantly positive at the 1% level, and the estimated coefficient is 2.879, which is much higher than that of the central city group. It indicates that digitalization plays a more prominent role in enhancing the quality of cooperative innovation in these cities. For non-central cities, their innovation resources are relatively scarce, and their network position is relatively marginal. Digital transformation effectively reduces the barriers for non-central cities to participate in cross-regional cooperation and improves the ability of information acquisition, collaborative research and development, and knowledge absorption. Therefore, these cities can more effectively integrate into a wider range of innovation networks and achieve a significant improvement in innovation quality. In addition, digital transformation can break geographical boundaries and provide non-central cities with more opportunities to collaborate with the outside world, further promoting their innovation capabilities. Therefore, in the process of promoting digital transformation, special attention should be paid to the construction of digital access capacity and collaborative platforms in non-core cities and areas. Through targeted digital infrastructure investment and innovation network empowerment, the formation of multi-level and multicenter patterns of innovation networks should be promoted, and regional innovation systems should be promoted to develop in a more balanced and inclusive direction.

Table 8. Heterogeneity analysis of the impact of digital transformation level on the quality of cross-regional cooperative innovation.

	(1) Eastern Region Inno-w	(2) Central Region Inno-w	(3) Western Region Inno-w	(4) Central Cities Inno-w	(5) Non-Central Cities Inno-w
Dige	2.869 *** (5.54)	1.219 *** (3.55)	8.501 *** (21.75)	1.221 (0.67)	2.879 *** (16.72)
Control	YES	YES	YES	YES	YES
Time Fixed	YES	YES	YES	YES	YES
City Fixed	YES	YES	YES	YES	YES
N	1078	846	457	332	2030
R ²	0.113	0.404	0.785	0.029	0.417
adj. R ²	0.010	0.328	0.754	−0.089	0.346

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusions

6.1. Research Conclusions

First, the evolution of network structure presents a pattern of scale expansion and small-world characteristics. During the sample period, the overall scale of the cross-regional cooperation network between cities in China continues to expand, and the network agglomeration continues to strengthen, showing an obvious small-world attribute. Beijing, Shanghai, Guangzhou, and Shenzhen occupy the core position of the network. Among them, Beijing is the absolute central city of cooperation and innovation in China. Xiamen, Hangzhou, Wuhan, Chengdu, Foshan, and other cities have formed regional cooperative innovation sub-networks through close connections with surrounding cities. Knowledge spillover and diffusion effects are significant. The network spatial structure is gradually

improved. The radiation and driving effect of core urban agglomeration is increasingly enhanced; meanwhile, the quadrilateral spatial structure is basically formed.

Second, digital transformation has a significantly positive impact on the quantity and quality of cross-regional cooperative innovation, and relational embeddedness plays a mediating role. The benchmark regression shows that the improvement in digital transformation level not only significantly increases the number of cross-regional cooperative patents but also greatly increases the frequency of patent citations. It shows that the quality improvement effect of digital enabling innovation is better than the incremental effect. The mechanism test finds that relational embeddedness is an important transmission path for digital transformation to promote the improvement in innovation. By enhancing the trust, reciprocity, and close interaction of innovation subjects between cities, digital transformation promotes the cross-regional transmission of high-quality, complex and tacit knowledge, thus realizing the optimization of innovation resource allocation and the improvement in the quality of intellectual property creation. The threshold effect model further reveals that the promoting effect of digital transformation on cooperative innovation presents nonlinear characteristics with increasing marginal effects. This shows that there is a critical condition for accelerating the release of digitalization's empowerment of innovation quality.

Third, the innovation enabling effect of digital transformation has significant regional heterogeneity and urban-level heterogeneity. We must note that the following findings are derived from subgroup comparisons and provide exploratory descriptive evidence rather than strict statistical tests of coefficient differences. A more rigorous approach would require formal interaction term models to confirm the statistical significance of these observed patterns. From the perspective of geographical location, the eastern region has formed a relatively mature cross-regional collaborative innovation model with a high level of digitalization. The level of digitalization in the central region is slightly lower, but the promotion effect on innovation quality is still significant. Although the overall situation of digitalization in the western region is low, the impact of digital transformation on cooperative innovation quality is the most prominent. It shows that digital technology has played a key compensatory role in breaking through geographical barriers and enhancing the connection between innovation subjects and external knowledge in western China. From the perspective of the urban administrative level, the effect of digital transformation of non-central cities on improving their innovation is significantly stronger than that of central cities. This reflects that digital technology has significantly enhanced the information acquisition ability and collaborative communication willingness of non-central cities. It also enables non-central cities to integrate into the national innovation network more effectively and accelerate the output and transformation of innovation achievements, thus bridging the innovation potential gap with central cities to a certain extent.

6.2. Further Discussion

This paper focuses on the impact of digital transformation on the quality of cross-regional cooperative innovation. Based on the data of A-share listed companies in the Shanghai and Shenzhen Stock exchanges and their cooperative patent information as innovation subjects, this paper systematically analyzes the cooperative network structure, influence mechanism and heterogeneity. Based on the conclusions of this paper, to fully release the innovation potential and optimize the pattern of regional collaborative innovation, the relevant policy suggestions and further discussion are as follows.

First, it is important to optimize the network spatial structure and strengthen the two-way linkage between the leading of core cities and the integration of edge cities. The study shows that central cities such as Beijing, Shanghai, Guangzhou, and Shenzhen play a key hub role in the cooperative innovation network, while non-central cities show stronger

catch-up power in the process of digital transformation. Therefore, on the one hand, China should give full play to the radiation driving function of core cities. Through policy guidance and resource allocation, central cities should be promoted to establish institutionalized and regular innovation cooperation mechanisms with surrounding and non-core node cities. Therefore, the cross-regional flow and sharing of knowledge, technology, talents and other factors should be promoted. On the other hand, further efforts can be made to improve the level and application capacity of digital infrastructure in non-core node cities. The embeddedness and participation ability of non-core node cities in the innovation network should be enhanced. In this way, the innovation potential difference between cities can be gradually narrowed, and the overall network efficiency can be optimized and improved.

Second, regional cooperation mechanisms should be deepened, and the collaborative evolution of digital transformation and relationship embeddedness should be promoted. Mechanism analysis shows that relational embeddedness is an important transmission path for digital transformation to enable cross-regional innovation improvement. Therefore, efforts should be made to build a cross-regional collaborative innovation system supported by digital technology and based on trust and reciprocity. In view of the heterogeneity of regional digital development level, differentiated policy supply should be implemented. The eastern region should continue to play a leading role in demonstration and explore cutting-edge models of digital enabling innovation. The central region needs to increase digital investment to make up for its shortcomings in innovation resources. The western region should make full use of the spatial compression effect of digital technology to break through the geographical barrier. In this way, it is possible to expand the channels of innovation connection with developed areas.

Third, the institutional guarantee system should be improved, and talent support and policy coordination for digital innovation should be strengthened. The enabling effect of digital transformation on innovation quality has stage characteristics, and there are critical conditions for accelerated release. This requires forward-looking and sustainable policymaking. On the one hand, the formulation of digital innovation development plans at the national and regional levels should be accelerated. The system can clarify the phased goals and key tasks and build a multi-dimensional policy support system covering fiscal, financial and taxation aspects. This will create a beneficial institutional environment for cross-regional cooperative innovation. On the other hand, talent is the core carrier of digital transformation and innovation activities. The government should improve the training, introduction, and incentive mechanism of digital talent and promote the collaborative education of universities, research institutions and enterprises. It is also beneficial to improve the digital literacy and technical ability of the innovation subject. This also provides a solid human capital guarantee for the high-quality development of cross-regional cooperation and innovation.

Digital transformation, as the core driving force of the new round of technological revolution and industrial transformation, is profoundly reshaping the global innovation landscape. Its promoting effect on cross-regional collaborative innovation has become a topic of widespread concern in the international community. This research still has certain limitations and can be further deepened in the following aspects in the future. Firstly, in terms of innovation quality assessment, a more comprehensive evaluation system for the effectiveness of cooperative innovation can be established by integrating multiple indicators such as technology conversion rate, market value, and social influence. Secondly, in terms of network structure, this paper only selects the cross-sectional data of network indicators for data analysis, focusing specifically on the changes in cooperative networks in a year. In the future, expanded studies will help to understand the connotation of the global

innovation network in the digital age more systematically. Research will also provide theoretical references and practical guidance for the design of innovation policies and international collaboration in different development contexts.

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