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Exploring the Spatial and Temporal Evolution Characteristics of Collaborative Innovation Network in Chengdu-Chongqing Urban Agglomeration and Its Impact on Regional Innovation Efficiency

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Abstract

The Chengdu-Chongqing urban agglomeration is designated by the national government as an innovation highland in central and western China, and thus plays a pivotal role in the country's innovation-driven development. However, research on collaborative-innovation mechanisms in the western region, and particularly on their economic consequences, remains scant. This paper analyzes 2015-2024 joint publications data from 24 administrative regions within the Chengdu-Chongqing cluster to examine the spatiotemporal evolution of its collaborative-innovation network and its impact on regional innovation efficiency. Using social-network analysis, we find that over the past decade the network's density has increased significantly, the average path length has shortened, and the clustering coefficient has remained stable—forming a "high-density, short-path, moderate-agglomeration" structure. Degree centralization first rose and then fell, indicating a maturing network. In terms of innovation efficiency, the cluster exhibits a "effective first and then ineffective". Regression results show that network density correlates positively with regional innovation efficiency, whereas centralization and average path length correlate negatively. Based on these findings, we propose strategic measures to optimize the Chengdu-Chongqing collaborative-innovation network for enhanced efficiency.

Keywords

Chengdu-Chongqing Urban Agglomeration, Network Characteristics, Collaborative Innovation Network, Innovation Efficiency

1. Introduction

Against the backdrop of globalization and accelerating regional economic integration, collaborative innovation has emerged as a pivotal driver of high-quality development for urban agglomerations, economic zones, and even nations. As a multi-level phenomenon spanning micro to macro scales, collaborative innovation fosters intraregional economies of scale, reduces transportation costs, enhances efficiency of transaction, generates knowledge spillovers, and strengthens regional resilience. Consequently, improving the efficiency of regional collaborative innovation networks is essential for harnessing the dividends of new quality productivity and advancing economic and technological exchanges within urban agglomerations. To achieve this objective, the Chinese government has explicitly outlined in the *14th Five-Year Plan* the need to optimize regional economic layouts, promote coordinated development, and implement major regional strategies to bolster the nation's overall scientific and technological competitiveness. Presently, China has established several key urban agglomerations for collaborative innovation, including Beijing-Tianjin-Hebei region, the Yangtze River Delta, the Pearl River Delta, the Shandong Peninsula, and Chengdu-Chongqing region, which play a role in facilitating intraregional integration and interaction.

The Chengdu-Chongqing urban agglomeration, as the strategic anchor of China's Western Development Strategy and a critical node in the national "Belt and Road" initiative, the construction of its collaborative innovation network and the enhancement of innovation efficiency are of great significance for the high-quality development of the western region of China. In practice, Sichuan and Chongqing are jointly advancing the development of this urban agglomeration, co-creating a "Tale of Two Cities" that will serve as a new growth pole for western China, a dynamic engine for national high-quality development, and a hub for economic activity, scientific and technological innovation, and reform and opening-up. This initiative will also cultivate a high-quality living environment, thereby providing robust support for China's "dual-circulation" development strategy. Therefore, exploring the collaborative innovation network and efficiency of the Chengdu-Chongqing urban agglomeration will facilitate the establishment of a cross-regional collaborative governance system. It will also further deepen the integration and complementation across economic, political, cultural, and scientific domains, optimize resource allocation efficiency, strengthen cross-regional industry-academia-research collaboration, and enhance the effectiveness of innovation transformation and institutional innovation.

Current academic research on collaborative innovation in urban agglomerations and economic zones mainly focuses on three areas. Firstly, it defines the basic characteristics of the collaborative innovation network in specific regions and clarifies the essential connotation of the collaborative innovation network. Secondly, it conducts empirical research to analyze the structure and influencing factors of the collaborative innovation network in urban agglomerations and economic zones. Thirdly, it examines the relationship between the collaborative innovation network and the efficiency of collaborative innovation. For the first type of research, Freeman (1991) first proposed the rudimentary concept of "collaborative innovation", arguing that it is a systematic innovation institutional arrangement generated through cooperative relationships among multiple entities. In the mutually permeating market or organizational relationships, there exists resource complementation and a clear connection mechanism for the entities as specific partnerships. Subsequently, the continuous progress of related research has enriched the connotation of this concept. For instance, Li, Sun, and Zhang (2021) further proposed the concept of a coordinated innovation network for urban agglomerations based on the study of collaborative innovation in the Beijing-Tianjin-Hebei region. Specifically, it refers to a cluster of urban innovation entities concentrated within a certain area, which, through the integration and flow of innovation resources, achieve division of labor, collaboration and integrated development, and form stable and continuous cooperative relationships. In the empirical analysis of the collaborative innovation network of urban agglomerations, domestic scholars have mostly constructed the measurement framework of the collaborative innovation network of urban agglomerations by using various research data, such as the joint publication data of urban agglomerations (Chen, Yang, & Gu, 2024), patent data (Huang, 2021; Wang, Sun, Du, & Li, 2020), incubation data (Liu, Qian, & Wang, 2023), and inter-provincial technology transaction data (Pan, Mu, & Zhai, 2022). They have also employed diverse empirical methods—including social network analysis, gravity models (Wang, Chen, & Huang, 2024; Li & Peng, 2020), cluster analysis, and knowledge complexity measurement (Xu, Zeng, & Wang, 2018)—to examine the collaborative innovation networks of China's three major urban agglomerations (Pan & Mu, 2022): the Beijing-Tianjin-Hebei region (Li et al., 2021), the Yangtze River Delta (Xu et al., 2018; Wang, Sun, Du, & Zhou, 2023), and the Pearl River Delta (Guangdong-Hong Kong-Macao Greater Bay Area) (Huang, 2021), and identified the relevant driving factors (Dai, Ding, Cao, Wu, & Wang, 2023).

In general, despite these advancements, existing research exhibits notable limitations that warrant further investigation. Firstly, in terms of the number of literature, the literature on the collaborative innovation of the Chengdu-Chongqing urban agglomeration is much scarcer than that of the Beijing-Tianjin-Hebei region, the Yangtze River Delta region, etc. There are certain research blind spots and policy deficiencies. Secondly, in terms of the scope scale, a large number of literature focus more on the impact of specific industries or green economic forms of the urban agglomeration on the collaborative innovation network. The literature based on the overall macro perspective of the urban agglomeration are insufficient, which leads to the scientific inference of the overall development experience of the urban agglomeration still being questionable. Finally, the relevant literature mainly focus on the collaborative innovation network of the urban agglomeration and its influencing factors. The exploration of the relationship between the collaborative innovation network and the collaborative innovation efficiency is still relatively shallow. Therefore, the marginal contribution of this paper lies in: Firstly, taking the Chengdu-Chongqing urban agglomeration as the research object, it innovatively examines the basic characteristics and evolution trend of the collaborative innovation network in this specific region from the joint publication data within the region, to a certain extent, filling the research gap of the collaborative network of Chengdu and even the western China urban agglomeration. Secondly, by comprehensively applying social network analysis, DEA data envelopment analysis, and Tobit model to fully identify the structural characteristics of the regional collaborative innovation network and its impact on regional innovation efficiency, it diagnoses the "high density - short path - moderate aggregation" networked collaborative innovation characteristics and the "first effective then ineffective" characteristics of collaborative innovation efficiency of the Chengdu-Chongqing urban agglomeration and the causes, providing more specific and effective ideas and directions for scientific policy-making.

2. Research Objects and Research Methods

2.1. Study Area

According to the Chengdu-Chongqing urban agglomeration Development Plan, the spatial scope of the Chengdu-Chongqing urban agglomeration includes 27 districts and counties in Chongqing Municipality, as well as parts of Kaixian County and Yunyang County, and 15 prefectural-level cities in Sichuan Province. Due to the issue of collaborative innovation, this paper selects 11 prefecture-level cities (including states) in Sichuan Province and 13 administrative counties in Chongqing Municipality, which have relatively close academic ties with the Chengdu-Chongqing urban agglomeration, including Chengdu Municipality, Zigong Municipality, Luzhou Municipality, Deyang Municipality, Mianyang Municipality, Suining Municipality, Neijiang Municipality, Leshan Municipality, Nanchong Municipality, Yibin Municipality and Dazhou Municipality, which are all under the jurisdiction of Sichuan Province, as well as Yuzheng District, which is all under the jurisdiction of Chongqing Municipality, as the object of the study, Wanzhou District, Fuling District, Shapingba District, Jiulongpo District, Nanan District, Beibei District, Yongchuan District, Hechuan District, Banan District, Yubei District, Qijiang District, and Bishan District. The scope of the spatial boundary of the specific research object is shown in **Figure 1**.

2.2. Research Methodology

At the methodological level, this study primarily employs Social Network Analysis (SNA) to measure the cohesion and evolutionary characteristics of the collaborative innovation network within the Chengdu-Chongqing urban agglomeration. SNA, grounded in social network theory, is a structured analytical approach designed to quantify the topological features of a network as a whole, thereby uncovering the connection patterns among nodes and the evolutionary dynamics of the system. This method has been widely applied in various fields such as trade

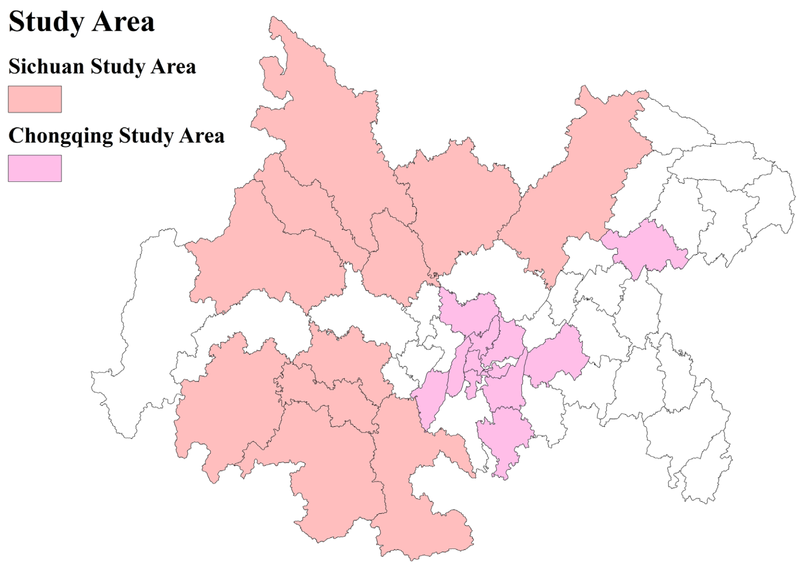

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Figure 1. Chengdu-Chongqing urban agglomeration research objects.

network analysis, transportation network optimization, information dissemination, and public health (Feng, Han, Shi, & Zhang, 2023), and is particularly well-suited for the dynamic monitoring of collaborative innovation networks in urban agglomerations.

2.2.1. Overall Network Analysis

In the study of collaborative innovation in urban clusters, the overall network analysis method serves as a mainstream methodology for measuring complex innovation systems. This approach effectively evaluates both the breadth and depth of cross-city innovation cooperation through systematic examination of four key indicators: network density, degree centralization, average path length, and clustering coefficient. These metrics collectively enable comprehensive assessment of the network's collaborative capacity from a global perspective.

Network density quantifies the coverage of inter-city innovation cooperation by measuring the closeness between nodes. Higher density indicates multiple channels for knowledge element flows. Moderate network density optimizes the balance between cooperation breadth and resource utilization efficiency. Degree centralization identifies core hub cities and their radiating influence within the innovation network. Average path length evaluates cross-regional knowledge transfer efficiency, with shorter paths signifying faster diffusion of innovation resources. The clustering coefficient characterizes the formation intensity of localized innovation clusters, revealing the knowledge spillover phenomenon in some regions.

Network density quantifies the level of connectedness among nodes in a network. It is defined as the ratio of the number of actual edges to the maximum possible number of edges in the network. A higher network density indicates a greater degree of closeness or interaction among nodes. The formula is as follows:

$$D = \frac{2E}{N(N-1)} \tag{1}$$

where D denotes the network density, E represents the number of actual edges, and N is the number of nodes, the value range of D is [0, 1]. A density value approaching 1 signifies a dense network, whereas a value nearing 0 indicates a sparse network.

Degree centralization measures the concentration of node connectivity within a network, reflecting whether innovation resources are concentrated in a few core hub cities. It is calculated using Freeman's centralization formula, which compares the actual network with a theoretically maximally centralized network:

$$C_D = \frac{\sum_{i=1}^{n}\left(C_{D\max} - C_{Di}\right)}{\max \sum_{i=1}^{n}\left(C_{D\max} - C_{Di}\right)} \tag{2}$$

here, $C_{D\max}$ denotes the highest degree centrality value among all nodes, C_{Di} represents the degree centrality of each individual node, and the denominator corresponds to the sum of differences in a star-shaped network. The index ranges between [0, 1], where higher values indicate greater concentration of network power in a few nodes, signifying stronger control of resource flows by core cities. Conversely, values approaching 0 suggest a more balanced distribution of connections among nodes.

The average path length measures the efficiency of connectivity between nodes in a network. It is calculated as the average of the shortest path lengths between all pairs of nodes. A shorter average path length indicates a more efficiently connected network, where information can be transmitted more rapidly. The formula is:

$$L = \frac{1}{\frac{N(N-1)}{2}} \sum_{i \neq j} d(i, j) \tag{3}$$

where L is the average path length and $d(i, j)$ is the shortest path from node i to j.

The clustering coefficient characterizes the local cohesiveness of nodes within a network. It is defined as the ratio of the number of actual connections among a node's neighbors to the maximum possible number of such connections. A higher clustering coefficient suggests that a node's neighbors are more tightly interconnected, indicating stronger local clustering or community structure.

The clustering coefficient for a single node is:

$$C_i = \frac{2e_i}{k_i(k_i - 1)} \tag{4}$$

where the clustering coefficient of node i, the actual number of edges between its neighbors, and its degree.

2.2.2. Individual Network Analysis

Individual-level network analysis focuses on the structural characteristics of nodes, measuring a city's position and connection patterns within the network to reveal its functional role and capacity for resource control in a collaborative innovation system. This approach is grounded in the concept of centrality from social network theory. Representative indicators include degree centrality, which reflects the strength of a node's direct connections; betweenness centrality, which indicates a node's role as a bridge between other nodes; and closeness centrality, which measures how centrally a node is positioned within the overall network. In multi-core innovation systems such as the Chengdu-Chongqing urban agglomeration, individual-level network analysis is effective in identifying the network connectivity strength of core hub cities, the bridging roles of secondary nodes, and the embedding paths of peripheral cities.

Degree centrality measures the number of other nodes to which a node is directly connected and reflects its local influence in the network. For node *i*, its degree centrality $C_D(i)$ is calculated as:

$$C_D(i) = \frac{d_i}{N-1} \tag{5}$$

here, d_i is the degree (number of directly connected edges) of node *i*, and *N* is the total number of nodes in the network. After standardization, the values range from 0 to 1, with higher values indicating a broader range of node connections.

Betweennerss centrality reflects the ability of a node to control the flow of information or resources in a network and is determined by calculating the proportion of nodes appearing on all shortest paths. The formula for this is:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{6}$$

here, σ_{st} is the total number of shortest paths from node *s* to *t*, and $\sigma_{st}(v)$ is the number of shortest paths passing through node *v*.

Closeness centrality reflects the average distance of a node from other nodes, with higher values indicating more efficient information transfer. The calculation formula is:

$$C_C(i) = \frac{N-1}{\sum_{j \neq i} d(i,j)} \tag{7}$$

here, $d(i,j)$ is the shortest path length from node *i* to *j*.

3. Analysis of Structural Characteristics and Evolution Law of Collaborative Innovation Network in Chengdu-Chongqing Urban Agglomeration

3.1. Basic Characteristics of Collaborative Innovation in Chengdu-Chongqing Urban Agglomeration

According to the theory of Regional Innovation Systems, the evolution of collaborative innovation networks within urban agglomeration is essentially a dynamic spatial reorganization of knowledge elements (Pan & Mu, 2022). As a key carrier of knowledge production and dissemination, inter-university joint publications serve as a direct reflection of the intensity of collaboration and the degree of network connectivity among regional innovation actors. To investigate the evolutionary patterns of the collaborative innovation network in the Chengdu-Chongqing urban agglomeration, we collected data on cross-regional joint publications between universities from 2015 to 2024. First, we identified all universities within the study area and constructed ten data tables—each corresponding to a specific year over the past decade—comprising 51 universities in total. Using the advanced search function of the China National Knowledge Infrastructure (CNKI), we conducted pairwise combinations of university names in the "author affiliation" field, limiting results mainly to the CNKI Chinese academic journals and conference paper databases. The number of joint publications retrieved for each university pair was manually recorded into the respective tables. These inter-university collaborations were then categorized according to their respective regions, allowing us to derive region-level co-authorship data. According to the First Law of Geography, both geographical proximity and institutional similarity are conducive to fostering innovation collaboration. Leveraging the radiative effects of its twin-core cities—Chengdu and Chongqing—the Chengdu-Chongqing urban agglomeration has gradually overcome administrative and spatial barriers through policy support, thereby promoting cross-regional flows of knowledge elements. Figure 2

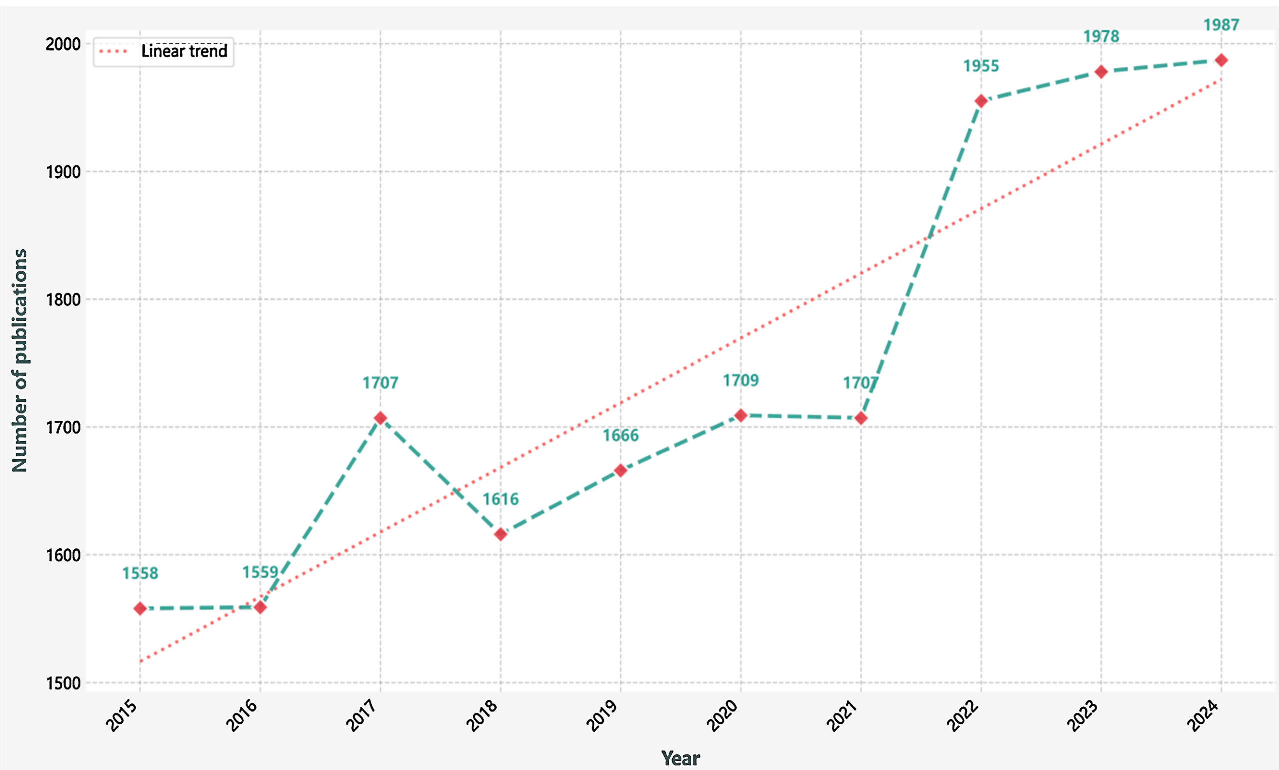
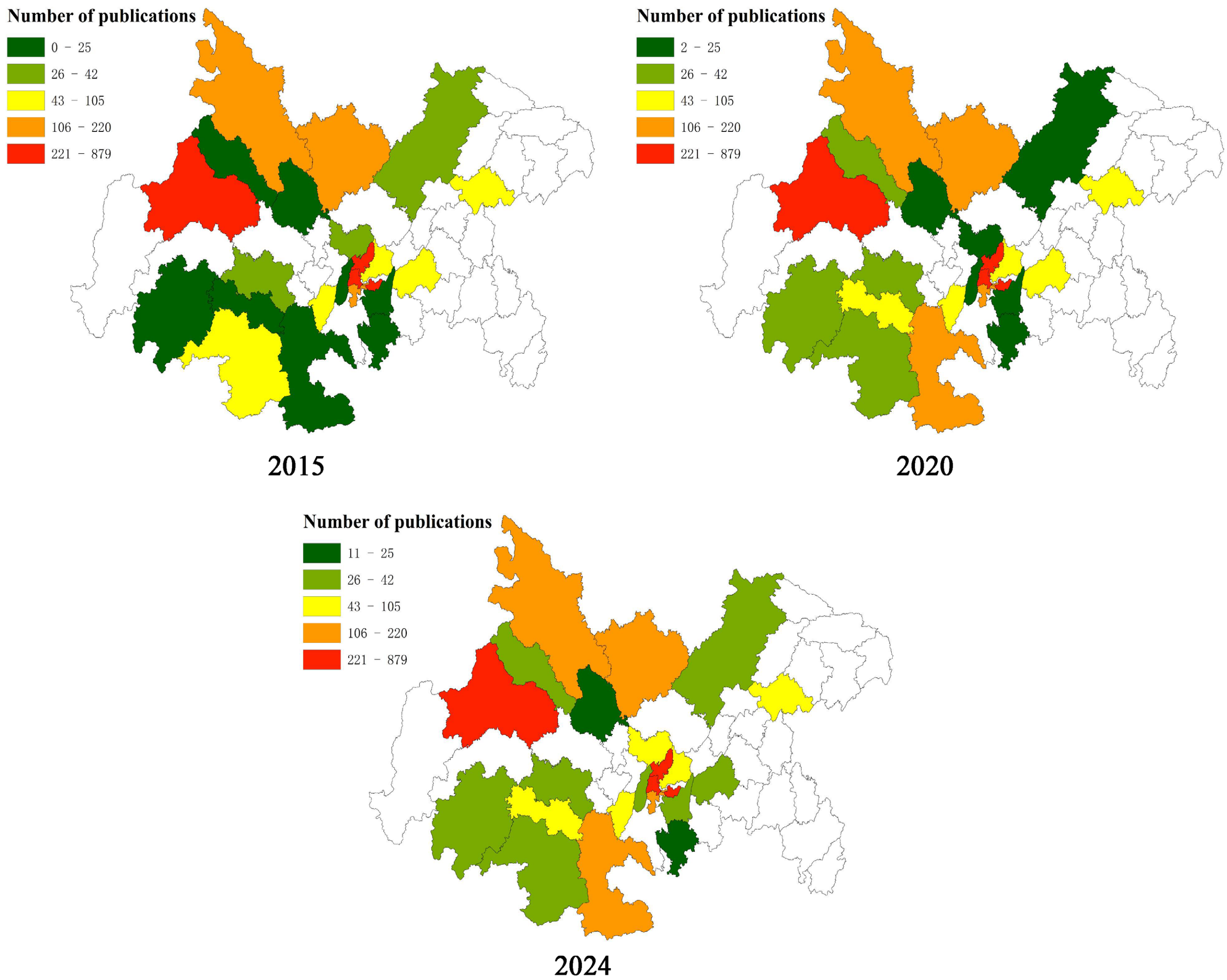


Figure 2. Evolutionary trend of the number of joint publications in Chengdu-Chongqing urban agglomeration over the years.

illustrates the dynamic growth trend of regional collaborative innovation. Figure 3 further reveals the spatial differentiation of innovation cooperation, which exhibits a "twin-core polarization" configuration, while simultaneously demonstrating a discernible diffusion trend toward secondary nodal cities.



Source: GS (2019) 1822. http://bzdt.ch.mnr.gov.cn/browse.html?picId=%224o28b0625501ad13015501ad2bfc0239%22.

Figure 3. Regional evolution of the number of joint publications in Chengdu-Chongqing urban agglomeration over the years.

As shown in Figure 2, at the macro level, the number of joint publications within the Chengdu-Chongqing urban agglomeration has increased significantly over the past decade, gradually forming a more integrated and cohesive collaborative innovation network. In 2015 and 2016, the number of joint publications remained relatively stable, with 1558 and 1559 records respectively. A notable increase occurred in 2017, reaching 1707, indicating an initial strengthening of collaborative activities. Although there was a slight decline to 1616 in 2018, the figures rebounded in subsequent years to 1666 in 2019 and 1709 in 2020. These short-term fluctuations did not disrupt the overall upward trend. From 2021 onward, the growth in joint publications became more pronounced. The number rose to 1955 in 2022 and further increased to 1978 and 1987 in 2023 and 2024, respectively. Notably, by 2024, the number of joint publications had reached 1987—an increase of nearly 30% compared to 2015. The substantial growth observed in recent years demonstrates increasingly intensive regional collaboration and knowledge exchange, indicative of sustained enhancement in both research capacity and academic influence.

As shown in Figure 3, the number of joint publications within the Chengdu-Chongqing urban agglomeration in 2015 was in an initial developmental phase. Most inter-city collaborations were concentrated in the low range (0 - 25 publications) and the lower-middle range (25 - 42 publications), indicating that collaborative innovation was still in its nascent stage, with limited frequency of cooperation among cities. During this period, only the core urban areas of Chengdu and central Chongqing exhibited relatively high levels of joint publications. A preliminary "dual-core drive" pattern of collaborative innovation began to emerge, yet peripheral cities remained minimally involved. By 2020, the region entered an expansion phase. The scope of the middle (43 - 105 publications) and upper-middle (100 - 220 publications) collaboration intervals expanded significantly. Cities such as Zigong and Luzhou saw notable increases in joint publications, indicating deeper integration into the collaborative innovation network. The number of regions in the low collaboration range decreased markedly. Innovation cooperation began to diffuse toward a more polycentric structure, with intensified collaborative activities among the core cities. By 2024, collaborative innovation had reached a relatively mature stage, with significantly strengthened inter-regional cooperation. The starting value of the lowest interval rose to 11 - 25 publications, reflecting deeper involvement of peripheral cities. The spatial coverage of the lower-middle (26 - 42 publications) and middle (43 - 105 publications) intervals further expanded. Sub-core innovation clusters, such as Hechuan District and Bishan District, demonstrated marked improvement in their capacity for cross-regional innovation cooperation. The connections between core cities and secondary nodes became increasingly close, facilitating knowledge flows beyond geographical constraints and significantly enhancing the efficiency of region-wide collaboration. This evolutionary process reflects a clear shift toward collaborative innovation, characterized by the gradual contraction of low-level cooperation intervals and the continuous expansion of higher-level intervals, signaling a consistent intensification of innovation collaboration across the entire region.

3.2. Characteristics of Chengdu-Chongqing Urban Agglomeration Collaborative Innovation Network Structure

3.2.1. Overall Network Characteristics

Based on co-authorship data, the innovation network indicators (Table 1) reveal significant dynamic evolutionary characteristics of the Chengdu-Chongqing urban agglomeration during the observation period. Network density increased from 0.280 in 2015 to a moderated 0.493 in 2024, indicating a gradual strengthening of

Table 1. Chengdu-Chongqing urban agglomeration collaborative innovation overall network indicators.

Year	Network Density	Degree Centralization	Average Path Length	Clustering Coefficient
2015	0.28	0.511	1.605	0.612
2016	0.359	0.462	1.548	0.668
2017	0.373	0.494	1.51	0.609
2018	0.344	0.573	1.593	0.562
2019	0.407	0.509	1.526	0.643
2020	0.442	0.561	1.565	0.6
2021	0.46	0.542	1.543	0.592
2022	0.486	0.466	1.525	0.628
2023	0.536	0.506	1.464	0.652
2024	0.493	0.506	1.507	0.604

cooperative relationships among regional innovation actors and a diversification of knowledge flow channels. Notably, despite the COVID-19 pandemic after 2020, the increase in network density remained pronounced, possibly due to national policies promoting the construction of the Chengdu-Chongqing economic circle.

The degree centralitzation exhibited a fluctuating pattern, reaching its extreme value in 2018 (0.573) and 2022 (0.466), reflecting the dynamic adjustment of core nodes within the innovation network. In the early stage (2015-2018), the network was characterized by a "center-periphery" structure dominated by the core districts of Chengdu and Chongqing. In the middle stage (2019-2021), secondary core cities such as Mianyang and Deyang began to emerge. In the later stage (2022-2024), a multi-core collaborative structure became evident.

In terms of network efficiency, the average path length declined from 1.605 in 2015 to 1.464 in 2023, marking a decrease of 8.8%. This suggests a notable improvement in the efficiency of cross-regional knowledge transmission. The continuous decline in path length from 2020 to 2023 may be attributed to advancements in transportation infrastructure and the adoption of digital technologies, which significantly shortened the temporal and spatial distances in intercity communication and resource exchange, thereby enhancing the diffusion efficiency of innovation resources.

The clustering coefficient remained consistently within the range of 0.56 to 0.67, higher than the expected value in a random network, confirming the small-world properties of the innovation network. This indicates clear clustering effects and the presence of intra-regional collaborative subnetworks. The network exhibits localized innovation clusters coexisting with cross-regional connections. Such a configuration not only preserves the advantages of local knowledge spillovers but also facilitates the recombination of heterogeneous knowledge through long-distance connections.

From the perspective of phased evolution, the Chengdu-Chongqing innovation network has undergone three main developmental stages. The period from 2015 to 2017 was marked by rapid network growth, characterized by a sharp increase in density and a steep decline in path length. The years 2018 to 2020 represented a period of structural adjustment, with significant fluctuations in degree centralization and path length, as well as a reversal in the trend of the clustering coefficient from rising to falling. From 2021 to 2024, the network entered an optimization and coordination phase, during which all indicators tended to converge and stabilize, demonstrating a mature network profile of "high density–short path–moderate clustering." This evolutionary trajectory reflects the transformation and upgrading of the regional innovation network toward a complex, nonlinear, and synergistic system.

3.2.2. Individual Network Characteristics

Table 2. Evolution of social network centrality of individual cities in Chengdu-Chongqing urban agglomeration.

City/Region	Particular year	Degree Centrality	Closeness Centrality	Betweenness Centrality
Chengdu	2015	0.783	0.639	0.121
	2024	0.957↑	0.958↑	0.109↓
Mianyang, prefecture level city in north Sichuan, Sichuan's second city	2015	0.348	0.489	0.003
	2024	0.522↑	0.676↑	0.011↑
Zigong, prefecture level city in Sichuan	2015	0	0.25	0
	2024	0.522↑	0.676↑	0.019↑
Yibin, prefecture level city in Sichuan	2015	0.304	0.479	0.004
	2024	0.391↑	0.622↑	0.003↓
Nanchong, prefecture level city in Sichuan	2015	0.478	0.535	0.035
	2024	0.609↑	0.719↑	0.017↓
Yubei, district of central Chongqing municipality, formerly in Sichuan	2015	0.522	0.548	0.022
	2024	0.478↓	0.657↑	0.011↓
Shapingba, district of central Chongqing municipality, formerly in Sichuan	2015	0.739	0.622	0.074
	2024	0.957↑	0.958↑	0.114↑
Nananqu, district of central Chongqing municipality, formerly in Sichuan	2015	0.522	0.548	0.018
	2024	0.913↑	0.920↑	0.104↑
Hechuan, suburban district of Chongqing municipality, formerly in Sichuan	2015	0.217	0.46	0
	2024	0.435↑	0.639↑	0.005↑
Fuling, suburban district of Chongqing municipality, formerly in Sichuan	2015	0.261	0.469	0
	2024	0.304↑	0.590↑	0.002↑

Note: The arrow symbols "↑" and "↓" in the text indicate the upward and downward trends of the indicators, and all values have been standardized according to the UCINET default methodology.

Based on interregional joint publications data from 2015 and 2024, centrality indicators were calculated to evaluate the structure of the collaborative innovation network. Among the 24 regions assessed, 10 typical regions were selected for further analysis based on their high centrality values or significant changes over time. The results, as presented in **Table 2**, demonstrate clear structural differentiation and dynamic evolution in the individual network roles of cities within the Chengdu-Chongqing urban agglomeration.

The polarization effect of core nodes has further intensified. Chengdu and the central urban areas of Chongqing (such as Shapingba District and Nan'an District) have continued to consolidate their positions as dual innovation engines. Chengdu's degree centrality surged from 0.783 to 0.957, representing a 22.2% increase and approaching the threshold of 0.958. This indicates a marked enhancement in its capacity to attract innovation resources and disseminate information. Shapingba District emerged as the most prominent node in terms of betweenness centrality, reaching 0.114, thereby forming a "Chengdu-Shapingba" dual-hub structure. Meanwhile, the siphoning effect of innovation resources by core areas may lead to a decline in degree centrality in secondary nodes such as Yubei District, which fell from 0.522 to 0.478, with a trend of increasing network polarization.

Peripheral cities are transitioning into secondary nodes. Traditional peripheral cities such as Zigong and Luzhou experienced breakthrough growth. Zigong's degree centrality rose from zero to 0.522, marking a remarkable increase of 170.4%. Mianyang, Neijiang, and Leshan all surpassed the 0.5 threshold in degree centrality, signaling the emergence of secondary innovation clusters. Districts such as Fuling and Hechuan also recorded significant increases in betweenness centrality through active cross-regional collaboration. This "periphery breakthrough" phenomenon reflects a structural shift in the collaborative innovation network, moving away from a double-core structure toward a multi-level, symbiotic node configuration.

The intermediary roles of core cities have undergone differentiated changes. Chengdu's betweenness centrality declined by 10.7%, while Shapingba and Nan'an Districts in Chongqing experienced substantial increases, indicating a strengthened bridging role of Chongqing's central urban areas in facilitating cross-regional innovation collaboration. Conversely, cities traditionally serving as intermediary nodes, such as Nanchong and Yibin, witnessed significant declines in betweenness centrality—by 51.4% and 25.0%, respectively—suggesting a structural adjustment in the pathways of resource flow within the network.

These evolutionary trends reveal that core cities in the Chengdu-Chongqing collaborative innovation network are promoting the development of secondary nodes through knowledge spillovers. At the same time, peripheral cities, benefiting from recent advancements in transportation and information infrastructure, are becoming more deeply embedded in the innovation network. Together, they are forming an innovation ecosystem characterized by "core leadership-multi-point support-integrated regional linkage."

3.3. Chengdu-Chongqing Urban Agglomeration Collaborative Innovation Network Evolution Patterns

According to regional economic theory, regions are systems composed of points, lines, surfaces, and networks, and their evolutionary process typically progresses through four stages: individual urban development, monocentric, polycentric, and ultimately, networked structures (Ma, Xu, & Hu, 2024). Assuming that the Chengdu-Chongqing urban agglomeration has reached the networked stage, this study explores the structural evolution of its collaborative innovation network. Based on co-authorship data, we employ network density, degree centralization, average path length, and clustering coefficient as key indicators, and the values of these indicators are denoted as m_1, m_2, m_3 and m_4. At the same time, the average values of the network structure indicators across all years, denoted as M_1, M_2, M_3, M_4, are used as benchmark references. By comparing the annual values of each indicator against these benchmarks, we identify distinct development stages of the urban agglomeration. Specifically, when $m_1 < M_1$, $m_2 < M_2$, $m_3 > M_3$, $m_4 < M_4$, the agglomeration is characterized as being in a weak-center stage. If $m_1 < M_1$, $m_2 > M_2$, $m_3 > M_3$, $m_4 < M_4$, it is categorized as a single-center stage. If $m_1 > M_1$, $m_2 > M_2$, $m_3 < M_3$, $m_4 > M_4$, it indicates a transition to a multi-center stage. Finally, when $m_1 > M_1$, $m_2 < M_2$, $m_3 < M_3$, $m_4 > M_4$, the network exhibits features of a networked stage.

Based on the joint publication data of the Chengdu-Chongqing urban agglomeration from 2015 to 2024, this study calculates the ten-year averages of the relevant network structure indicators (Table 1) to establish the benchmark values for assessing the relative level of development across years. The computed benchmarks are as follows: network density $M_1 = 0.418$, degree centralization $M_2 = 0.513$, average path length $M_3 = 1.539$, and clustering coefficient $M_4 = 0.617$. By comparing each year's indicator values against these benchmarks, the corresponding stage of innovation network evolution can be identified (Table 3).

Table 3. Chengdu-Chongqing urban agglomeration collaborative innovation network stage determination.

Particular year	Network density	Degree Centralization	Average path length	Clustering Coefficient	Developmental stage
2015	0.280↓	0.511↓	1.605↑	0.612↓	Phase I
2018	0.344↓	0.573↑	1.593↑	0.562↓	Phase II
2021	0.460↑	0.542↑	1.543↓	0.592↓	Phase III
2024	0.493↑	0.506↓	1.507↓	0.604↑	Phase IV

Note: ↑ indicates higher than the baseline value and ↓ indicates lower than the baseline value.

As shown in Table 3, in 2015, the innovation network of Chengdu-Chongqing urban agglomeration showed typical weak center characteristics. The network density (0.280) and degree ocentralization (0.511) are both significantly lower than the benchmark value, indicating that the innovation cooperation between cities is sparse and lacks core hubs. The average path length (1.605) reaches a ten-year peak, reflecting that knowledge flows need to be relayed through multiple nodes, which is inefficient. The clustering coefficient (0.612) is close to the benchmark but does not reach the mean, indicating that local cooperation has not yet formed stable clusters. This stage is in line with the characteristics of the theory of "individual city development", in which cities focus on internal innovation and cross-city collaboration is not yet normalized.

By 2018, the innovation network of Chengdu-Chongqing urban agglomeration presents the characteristics of a single-center urban agglomeration in stage II, with the degree centralization jumping to 0.573, which is 11.7% higher than the benchmark, showing that the polarization effect of the dual core of Chengdu and Chongqing is significantly enhanced. However, the network density (0.344) and clustering coefficient (0.562) are still lower than the benchmark, and the average path length (1.593) remains high, indicating that innovation resources are overly concentrated in the core cities and the development of secondary nodes lags behind. At this stage, a "core-periphery" structure is evident, in which the dual-core cities have formed innovation poles through policy-driven initiatives. However, their capacity to radiate and drive surrounding areas has not yet been fully realized.

In 2021, the innovation network of Chengdu-Chongqing urban agglomeration presents the characteristics of Stage III, marked by a polycentric urban structure. The network density (0.460) breaks through the benchmark value for the first time, and the average path length (1.543) is shortened below the benchmark, marking the increase in the frequency of cross-city collaboration and the improvement in the efficiency of information flow. The degree centralization (0.542) remains high, but the clustering coefficient (0.592) is still lower than the average value, reflecting that sub-nodes such as Mianyang and Deyang are beginning to rise, but the local innovation clusters still need to be improved. At this stage, the situation of "multi-core symbiosis" is presented, with innovation resources shifting from unipolar agglomeration to gradient diffusion.

In 2024, the innovation network of Chengdu-Chongqing urban agglomeration reaches stage IV, showing the characteristics of networked urban agglomeration. The network density (0.493) and clustering coefficient (0.604) exceed the benchmark, the average path length (1.507) drops to the lowest in ten years, and the degree centralization (0.506) returns to the equilibrium level. It shows that the innovation network manifests a multi-tiered interconnected structure characterized by core, sub-center, and periphery layers, and the knowledge flow breaks through the geographic attenuation effect and realizes cross-regional efficient synergy. This stage marks the completion of the transformation of Chengdu-Chongqing urban agglomeration from "polycentric" to "networked", and the structural resilience is significantly enhanced.

4. The Impact of Chengdu-Chongqing Urban Agglomeration Collaborative Innovation Network on Collaborative Innovation Efficiency

4.1. Measuring the Efficiency of Collaborative Innovation in Urban Agglomerations

In the following, we adopt the data envelopment analysis (DEA) method to measure the efficiency of collaborative innovation in the Chengdu-Chongqing urban agglomeration. The DEA model is a nonparametric method for assessing the efficiency of decision-making units with multiple inputs and multiple outputs. From a practical perspective, data envelopment analysis (DEA) offers a powerful tool for accurately identifying inefficiency sources. When overall technical efficiency shows a declining trend, DEA can decompose the efficiency loss into pure technical efficiency and scale efficiency, thereby enabling targeted optimization of resource allocation to address specific areas of weakness. Furthermore, by collecting continuous time-series data, DEA facilitates dynamic monitoring of policy impacts. Through intertemporal DEA analysis, policymakers can track the evolution of efficiency over time and assess the long-term effects of policy interventions.

The specific measurement process proceeds as follows: firstly, based on the input-output logic of innovation activities, we select the full-time equivalent of R&D personnel and the internal R&D expenditure for each city as input indicators, while using the number of co-published academic papers between cities is as output indicators. The input data are sourced from the official statistical yearbooks of the National Bureau of Statistics and the statistical bureaus of Sichuan and Chongqing, and the output data are extracted and organized from the publication database of China Knowledge Network (CNKI). For missing R&D data in certain years, linear interpolation is applied for imputation. Subsequently, the CCR model with constant returns to scale (CRS) and the BCC model with variable returns to scale (VRS) are constructed respectively, and the comprehensive technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) are measured by the two-stage combination framework. The CCR model determines the input minimization ratio θ to evaluate TE without convexity constraints, reflecting the urban agglomeration's overall resource allocation efficiency. In contrast, the BCC model incorporates the convexity constraint $\sum\lambda = 1$ to isolate PTE from scale effects, thereby capturing technical management proficiency. For each decision-making unit (DMU), the objective function θ is derived iterative linear programming. In the BCC model, the weighted sum of reference units' inputs must not exceed θ times the current unit's inputs, and the weighted sum of outputs must not fall below the current unit's actual outputs. After completing the two-stage model solution, the scale efficiency is calculated by the formula SE = TE/PTE. Finally, we assess the effectiveness of DEA in each city based on the efficiency scores. This method realizes the model solution through the PuLP library of Python, with algorithms strictly following the classical framework of Charnes-Cooper-Rhodes and Banker-Charnes-Cooper.

The DEA framework employs a two-stage composite model. In the first stage, an input-oriented BCC model (Banker-Charnes-Cooper model) is implemented under the variable returns to scale (VRS) assumption to estimate pure technical efficiency (PTE). This measurement captures the technical and managerial efficiency while excluding the influence of scale factors. The objective function is assumed to be $\min \theta_{\text{BCC}}$, and then the constraints are:

$$\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_{\text{BCC}} x_{i0}, & \forall i = 1, \cdots, m \ (\text{Input constraints}) \\ \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0}, & \forall r = 1, \cdots, s \ (\text{Output constraints}) \\ \sum_{j=1}^{n} \lambda_j = 1, & (\text{Convexity constraint}) \\ \lambda_j \ge 0, & j = 1, 2, \cdots, n \ (\text{Non-negativity constraints}) \end{cases} \tag{8}$$

x_{i0} is observed quantity of the *i*-th input for the evaluated DMU. y_{r0} is observed quantity of the *r*-th output for the evaluated DMU. λ_j is intensity weights assigned to DMU *j*. θ_{BCC} is technical efficiency score. m is number of inputs. s is number of outputs. n is number of decision-making units (DMUs).

In the BCC model, the convexity constraint allows the production frontier to exhibit non-proportional variation. The efficiency value $\theta_{\text{BCC}} \in (0,1]$ reflects the level of pure technical management excluding the effect of scale. When $\theta_{\text{BCC}} = 1$, it indicates that the decision-making unit (DMU) is at the technologically efficient frontier.

In the second stage, the CCR model (Charnes-Cooper-Rhodes model) is used to calculate the combined technical efficiency (TE) under the assumption of Constant Returns to Scale (CRS), which incorporates the joint effect of scale effect and technology. Let the objective function be $\min \theta_{\text{CCR}}$, and the constraints be:

$$\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_{\text{CCR}} x_{i0}, & \forall i = 1, \cdots, m \ (\text{Input constraints}) \\ \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0}, & \forall r = 1, \cdots, s \ (\text{Output constraints}) \\ \lambda_j \ge 0, & j = 1, 2, \cdots, n \ (\text{Non-negativity constraints}) \end{cases} \tag{9}$$

x_{i0} is observed quantity of the *i*-th input for the evaluated DMU. y_{r0} is observed quantity of the *r*-th output for the evaluated DMU. θ_{CCR} is technical efficiency score. m is the number of inputs. s is number of outputs. n is the number of decision-making units (DMUs).

Compared to BCC, CCR removes the convexity constraint ($\Sigma\lambda = 1$) and the production frontier expands radially. The efficiency value $\theta_{\text{CCR}} \in (0,1]$ characterizes the combined technical efficiency that includes scale effects. $\theta_{\text{CCR}} = 1$ indicates that the DMU achieves both technical and scale efficiency.

Finally, scale efficiency is calculated from the two-stage results:

$$\text{SE} = \frac{\text{TE}_{\text{CCR}}}{\text{PTE}_{\text{BCC}}} \tag{10}$$

When TE = 1 and SE = 1, the production unit attains simultaneous technical efficiency and scale optimality. If SE < 1, there exists scale inefficiency and the input scale needs to be adjusted. If TE < 1, the contribution difference between pure technical efficiency and scale efficiency should be further analyzed.

With the above methods, we analyze the collaborative innovation efficiency of urban agglomerations from the dimensions of comprehensive technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE). Among them, comprehensive technical efficiency characterizes the overall synergistic effectiveness of the regional innovation system. When TE = 1, it indicates that it reaches the effective state of DEA, signifying optimal resource allocation and production efficiency. Pure technical efficiency (PTE) measures the contribution of technological innovation capabilities to efficiency after controlling for scale effects. In contrast, scale efficiency (SE) reflects the alignment between the actual production scale and the optimal scale under a given technological level. When SE < 1, it indicates potential efficiency gains through scale adjustment to enhance the innovation system's output performance. Based on the calculation results, some regions with significant numerical changes and relatively large values were selected as representative cases, as shown in Table 4.

Table 4. DEA measurement results by region.

City/Region	TE			PTE			SE		
	2015	2020	2024	2015	2020	2024	2015	2020	2024
Jiulongpo	0.18	0.104	0.089	0.188	0.111	0.093	0.961	0.936	0.96
Beibei	0.456	0.212	0.236	0.844	0.26	0.329	0.541	0.814	0.718
Nanchong	0.766	0.536	0.418	0.778	0.543	0.429	0.985	0.987	0.974
Nan'an	0.407	0.383	0.281	0.63	0.67	0.431	0.645	0.571	0.652
Hechuan	0.145	0.043	0.149	0.54	0.27	0.244	0.269	0.158	0.609
Banan	0	0.028	0.119	0.2	0.136	0.202	0	0.206	0.59
Deyang	0.012	0.031	0.031	0.084	0.057	0.062	0.141	0.549	0.496
Chengdu	0.107	0.083	0.068	0.52	0.897	0.895	0.205	0.092	0.076
Shapingba	0.63	0.31	0.245	1	0.484	1	0.63	0.642	0.245
Luzhou	0	0.395	0.356	0.416	0.405	0.359	0	0.976	0.993
Mianyang	0.065	0.044	0.031	0.07	0.047	0.034	0.93	0.936	0.893
Dazhong	0.347	0.086	0.102	1	0.345	0.277	0.347	0.25	0.37

From Table 4, the distribution of Total Efficiency (TE) exhibits a clear "polarization" pattern. In 2015, Nanchong and Shapingba District recorded high TE values of 0.766 and 0.63, respectively, approaching the efficiency frontier. However, both experienced notable efficiency declines over the subsequent years, falling to 0.418 and 0.245 by 2024, suggesting diminishing marginal returns in their collaborative innovation systems. In contrast, Chengdu, despite leading in total R&D investment, saw its TE value consistently decrease from 0.107 in 2015 to 0.068 in 2024. The city's persistently low Scale Efficiency (SE) reflects severe inefficiencies, likely due to over-investment and redundant resource allocation. Meanwhile, cities like Luzhou and Banan significantly improved their Scale Efficiency (SE) through scale optimization. Luzhou, in particular, reached an SE of 0.993, nearing DEA effectiveness.

Pure Technical Efficiency (PTE), which reflects the capacity for technological transformation and management, varied widely across cities. In some cases, it showed a negative correlation with input levels. For instance, Shapingba maintained an optimal PTE of 1.0 in both 2015 and 2024, yet experienced a sharp decline to 0.484 in 2020, possibly due to policy misalignment or technological discontinuity. Cities such as Deyang and Jiulongpo exhibited persistently low PTE, underscoring weak technology conversion capabilities and a pressing need to enhance university-industry collaboration. The substantial volatility in Beibei's PTE suggests intermittent failures in its technology management strategies.

Scale Efficiency (SE), reflecting the appropriateness of input scale. Cities like Nanchong and Jiulongpo consistently maintained SE values above 0.95, close to DEA effectiveness. In contrast, Chengdu's SE fell to just 0.076 in 2024, implying significant diseconomies of scale and ineffective resource deployment. However, cities such as Hechuan and Banan improved their SE through dynamic input adjustments, with SE values rising from 0.269 and 0 to 0.609 and 0.59, respectively.

Overall, between 2015 and 2024, TE declined in 67% of the observed cities and PTE declined in 83%, highlighting widespread inefficiencies in technology management. For example, Dazhou's PTE dropped sharply from 1.0 to 0.277, while its SE showed only a slight increase, indicating that technological regression was the primary driver of efficiency loss. Although Mianyang experienced declines in both PTE (from 0.07 to 0.034) and SE (from 0.93 to 0.893), its scale-driven innovation model still outperformed many peer cities.

4.2. Analysis of the Evolution of Overall Collaborative Innovation Efficiency in Chengdu-Chongqing Urban Agglomeration

In this study, the full-time equivalent R&D personnel and R&D expenditure of 24 regions from 2015-2024 are used as input indicators. Additionally, the number of joint publications is used as an output indicator. These variables are incorporated into the DEA model to evaluate efficiency. The measurement results are presented in Table 5.

According to Table 5, a clear downward trend is observed in total technical efficiency (TE). TE declined significantly from 1.0 in 2015 to 0.64 in 2024, representing a 36% reduction. The period from 2015 to 2020 saw a relatively rapid decline, with an average annual decrease of 6.3%. However, the rate of decline moderated significantly to 0.9% per year. These trends demonstrate a progressive weakening of overall collaborative innovation efficiency within the urban agglomerations, indicative of emerging bottlenecks in both resource integration capabilities and technology transfer proficiency. Pure technical efficiency (PTE) remained relatively high despite fluctuations. In most years, PTE approached or

Table 5. Co-innovation efficiency by year, 2015-2024.

Particular year	TE	PTE	SE
2015	1	1	1
2016	0.972	0.975	0.997
2017	0.977	1	0.977
2018	0.802	0.809	0.991
2019	0.746	0.759	0.983
2020	0.72	0.74	0.973
2021	0.657	0.672	0.977
2022	0.697	0.988	0.706
2023	0.683	1	0.683
2024	0.64	0.934	0.685

reached 1.0, suggesting generally sound management and technological capabilities. However, a sharp drop to 0.672 in 2021 may reflect the impact of external shocks such as the COVID-19 pandemic or policy implementation issues. The subsequent rebound to 0.988 in 2022 points to a partial recovery in technological conversion capacity. Scale efficiency (SE), by contrast, deteriorated notably in the later years. From 2015 to 2021, SE remained stable between 0.977 and 0.997, close to DEA efficiency. However, it dropped sharply after 2022, reaching only 0.685 in 2024. This suggests increasing imbalances between input scale and resource allocation, possibly due to excessive agglomeration in core cities and insufficient coordination with peripheral areas, leading to diseconomies of scale.

In terms of DEA effectiveness, 2015 was the only year of full efficiency, with TE, PTE, and SE all equal to 1.0, indicating optimal performance in both technical and scale dimensions. However, efficiency declined steadily thereafter. By 2024, only PTE (0.934) remained close to the efficient frontier, while TE (0.64) and SE (0.685) deviated significantly, highlighting growing inefficiencies. Overall, the DEA results suggest a shift from "initial efficiency" to "subsequent inefficiency" in the collaborative innovation system of the Chengdu-Chongqing urban agglomerations. While technical efficiency was intermittently sustained, increasing scale redundancy and resource misallocation have become the dominant factors driving efficiency losses, ultimately constraining collaborative performance through emerging diseconomies of scale.

4.3. Analysis of the Impact of Collaborative Innovation Networks in Urban Agglomerations on Innovation Efficiency

4.3.1. Theoretical Analysis of the Impact of Collaborative Innovation Networks on Innovation Efficiency

From the previous analysis, it can be seen that the structure of collaborative innovation network systematically influences the efficiency of collaborative innovation in urban agglomerations through a multi-level and multi-path approach. Specifically, there is the following mechanism logic:

First, high network density significantly enhances the accessibility and fluidity of information flows among cities. A densely connected structure reduces search costs for technologies and partners, enabling rapid knowledge transmission through shorter linkages and minimizing time and transaction costs (Liu, 2020). Furthermore, diverse and redundant connections prevent over-reliance on single partners, facilitating multi-channel knowledge acquisition and more efficient R&D resource allocation. Repeated cooperation within high-density networks fosters mutual trust and informal norms, which reduce institutional transaction costs—such as those related to contracting and IP protection, thus creating a conducive environment for sustained innovation. Accordingly, network density is positively associated with the collaborative innovation efficiency of urban agglomeration.

Second, high network centrality means resources and information are concentrated in a few core cities, enabling large-scale production and cross-regional integration but relegating peripheral cities to passive information recipients. Over time, this unidirectional knowledge flow weakens the absorptive capacity of edge-node regions, induces talent outflow and capital shortages, exacerbates interregional imbalances, and undermines the scale efficiency (SE) of the urban cluster (Xia, Xie, & Fu, 2017). Moreover, a longer average path length delays knowledge transfer, increases the likelihood of noise or distortion at each exchange, and diminishes the responsiveness and market adaptability of collaborative innovations, further constraining SE. In contrast, a polycentric-nested or flat network structure disperses resource control while preserving accessibility, shortens path lengths, and flattens decision-making hierarchies. Such configurations enable broader city participation in resource allocation, stimulate intraregional collaboration, and thus enhance both comprehensive technical efficiency (TE) and scale efficiency (SE). Network centrality and average path length are negatively correlated with scale efficiency (SE), while technical efficiency (TE) is positively correlated with scale efficiency (SE). Consequently, both network centrality and path length also exhibit negative correlations with TE.

Thirdly, from the perspective of network clustering, a high clustering coefficient enhances pure technical efficiency (PTE) by fostering strong local connections based on geographic proximity, industrial linkages, or historical collaboration. These high clustering subgroups promote trust, facilitate the smooth exchange of tacit knowledge, and enable rapid synchronization of ideas and technical details. Frequent micro-level collaborations allow for accelerated trial-and-error processes, converting tacit experiences into explicit, replicable outcomes. Intra-cluster homogeneity reduces partner-matching costs, while bridge nodes maintain inter-cluster connectivity, balancing technical depth with diversity. As a result, the clustering coefficient is positively correlated with pure technical efficiency (PTE). Given the positive relationship between pure technical efficiency

(PTE) and comprehensive technical efficiency (TE), clustering also contributes to the improvement of technical efficiency (TE).

Based on the mechanism of how innovation network structure affects collaborative innovation efficiency, the following hypotheses are proposed.

Hypothesis 1 (H1): Network density positively influences urban cluster collaborative innovation efficiency. Dense networks accelerate knowledge search and matching while reducing systemic risks through diversified connections, providing stable institutional support.

Hypothesis 2 (H2): Network centralization and average path length negatively impact urban cluster collaborative innovation efficiency. Excessive centralization and long transmission paths create a siphon effect, slowing knowledge flow and hindering the realization of economy-wide collaborative benefits.

Hypothesis 3 (H3): The clustering coefficient positively correlates with urban cluster collaborative innovation efficiency. Highly clustered subgroups foster trust and tacit understanding, facilitating knowledge sharing and technological iteration, maximizing local collaboration efficiency.

4.3.2. Model Construction

In empirical research, when the dependent variable is subject to truncation or censoring, traditional linear regression models may yield biased estimates due to the failure to account for the limited nature of the data distribution. To address this issue, Tobin proposed the Tobit model (also known as the censored regression model) in 1958, which introduces a latent variable framework to capture the nonlinear relationship between the censored dependent variable and the independent variables. This model is particularly effective in handling cases where the dependent variable is censored at a certain threshold. The standard Tobit model assumes that the observed dependent variable y_i is determined by an underlying continuous latent variable y_i^*, which follows the linear relation:

$$y_i^* = X_i'\beta + \varepsilon_i \sim N\left(0, \sigma^2\right) \tag{11}$$

here, X_i' denotes the vector of independent variables, β is the parameter vector to be estimated, and ε_i is the error term assumed to follow a normal distribution. Due to the presence of truncation (or censoring) in the data, the observed dependent variable y_i takes the following form:

$$y_i = \begin{cases} y_i^*, & y_i^* > c \\ c, & y_i^* \le c \end{cases} \tag{12}$$

In the Tobit model, c represents the truncation point, which is typically set to zero when the dependent variable cannot take negative values. The estimation of the Tobit model primarily relies on the method of maximum likelihood, with its likelihood function fully accounting for both truncated and non-truncated observations. This enables the parameter estimates to be both efficient and consistent. By constructing and estimating the Tobit model, researchers can effectively capture the distributional characteristics of the dependent variable within the truncated range and more accurately describe the true effects of the independent variables.

This study employs the efficiency of collaborative innovation (TE), measured using the data envelopment analysis (DEA) model, as the dependent variable. The TE value reflects the overall efficiency of collaborative innovation within urban agglomeration. Similar to traditional linear regression, the Tobit model is employed to examine the relationship between independent and dependent variables, thereby providing empirical support for policy formulation. However, since technical efficiency (TE) values are truncated within the [0, 1] interval, conventional linear regression models are prone to biased parameter estimates. To address the boundary issue of the dependent variable, the Tobit model is adopted, enabling a more accurate assessment of how overall network structural characteristics influence efficiency. This approach helps mitigate estimation bias and yields results that are more reflective of real-world policy contexts.

The core explanatory variables include indicators of the overall network structure of the Chengdu-Chongqing urban agglomeration, such as network density, network centralization, average path length, and clustering coefficient. These variables are used to assess the influence of network structure on collaborative innovation efficiency.

The model also controls for educational expenditure. Since collaborative innovation efficiency is measured using co-authorship data, which is closely related to educational investment, it is important to account for education spending. Educational investment directly affects the scale and quality of high-caliber talent development, plays a critical role in human capital accumulation, and serves as a foundational guarantee for enhancing regional innovation capacity. The variable design is detailed in Table 6.

Table 6. Table of variables.

Variant	Notation	Name	Clarification
Dependent variable	TE	Co-innovation efficiency	Calculated using DEA model
Explanatory variable	DEN	Network density	Derived from Ucinet analysis
	CEN	Degree centralization	
	PATH	Average path length	
	CC	Clustering coefficient	
Control variable	EDU	Expenditure on education	Annual expenditure (unit: 100 million CNY)

4.3.3. Calculation Results

The empirical analysis of the factors influencing collaborative innovation efficiency in the Chengdu-Chongqing urban agglomeration is conducted using the Tobit model, implemented in Stata 18.0. The model is specified as follows:

$$\mathrm{TE}_t 1 = \beta_0 + \beta_1 \mathrm{DEN}_t + \beta_2 \ln \mathrm{EDU}_t + \varepsilon_t \tag{13}$$

$$\mathrm{TE}_t 2 = \beta_0 + \beta_1 \mathrm{CEN}_t + \beta_2 \ln \mathrm{EDU}_t + \varepsilon_t \tag{14}$$

$$\mathrm{TE}_t 3 = \beta_0 + \beta_1 \mathrm{PATH}_t + \beta_2 \ln \mathrm{EDU}_t + \varepsilon_t \tag{15}$$

$$\mathrm{TE}_t 4 = \beta_0 + \beta_1 \mathrm{CC}_t + \beta_2 \ln \mathrm{EDU}_t + \varepsilon_t \tag{16}$$

here, TE_t denotes the value of collaborative innovation efficiency of urban agglomeration in year *t*, which is measured by DEA model. On the right side of the equation are the explanatory variables influencing collaborative innovation efficiency in year *t*. The intercept term is β_0. β_1 and β_2 are the regression coefficients, and ε_t is the random error term assumed to follow a normal distribution. The estimation results of the model parameters are shown in Table 7.

Table 7. Tobit regression results.

Variant	(1) model1 TE	(2) model2 TE	(3) model3 TE	(4) model4 TE
DEN	0.990*			
	(0.452)			
ln_EDU	−1.292***	−0.826***	−0.989***	−0.844***
	(0.229)	(0.0756)	(0.0721)	(0.0895)
CEN		−0.806***		
		(0.204)		
PATH			−0.968***	
			(0.245)	
CC				0.590
				(0.376)
Constant	10.39***	7.608***	9.944***	6.965***
	(1.602)	(0.646)	(0.798)	(0.771)
var	0.00145**	0.00117**	0.00102**	0.00169**
	(0.000447)	(0.000419)	(0.000438)	(0.000670)
F-statistic	47.8549	60.6826	96.7796	49.3312
p-value	0.0000	0.0000	0.0000	0.0000

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

4.3.4. Discussion of Results

The empirical results (Table 7) based on the Tobit model reveal that the collaborative innovation efficiency (TE) of the Chengdu-Chongqing urban agglomeration is significantly influenced by network structural characteristics, partially confirming the proposed hypotheses. The detailed analysis is as follows:

First, the regression coefficient for network density (DEN) is 0.99 and statistically significant at the 5% level, supporting Hypothesis H1. This suggests that denser innovation networks positively impact technical efficiency (TE). A high-density network fosters deeper integration of peripheral nodes and broadens the scope of intercity innovation collaboration, facilitating the cross-regional flow of knowledge and enhancing resource allocation efficiency. Dense connections shorten information transmission paths, diversify collaboration channels, and reduce the transaction costs associated with knowledge search and matching. Moreover, frequent interactions enhance mutual trust among cities, providing institutional support for the exchange of tacit knowledge.

Second, the regression coefficients for network centralization (CEN) and average path length (PATH) are −0.806 and −0.968, respectively, both significant at the 1% level, thus validating Hypothesis H2. This indicates that excessive concentration of innovation resources in core cities undermines the scale efficiency of peripheral regions, while longer transmission paths raise the spatial and temporal costs of knowledge diffusion. For example, although increased betweenness centrality in districts like Shapingba (Chongqing) and Chengdu strengthens the dual-core hub function, it also intensifies the "core-periphery" asymmetry, relegating peripheral cities to passive roles.

Third, the regression coefficient for the clustering coefficient (CC) is 0.59, but only marginally significant at the 15% level, failing to support Hypothesis H3. This may be attributed to the relatively short study period (ten years) or reflect the "closed" nature of local innovation subgroups within the cluster. While high clustering suggests strong localized collaboration (e.g., within Chengdu-Deyang-Mianyang or northeastern Chongqing clusters), the lack of weak ties between subgroups leads to knowledge homogeneity and path dependence. For instance, although cities like Mianyang and Deyang are active within their local clusters, limited collaboration with peripheral cities hampers the transformation of localized knowledge into broader innovation efficiency.

Fourth, regarding the control variables, the regression coefficient for education expenditure (ln_EDU) is significantly negative, indicating that increased investment in education may, counterintuitively, hinder the improvement of collaborative innovation efficiency in the Chengdu-Chongqing urban agglomeration. This outcome may stem from multifaceted underlying contradictions. First, the spatial allocation of educational resources is highly imbalanced. Core cities such as Chengdu and Chongqing attract a disproportionate share of high-quality universities and research institutions, while peripheral cities like Zigong and Luzhou face persistent underinvestment. This leads to a polarized distribution of human capital—core cities experience oversupply and intense competition, while peripheral regions struggle to build a robust talent base, undermining the region-wide potential for collaborative innovation. Second, the misalignment between the education system and the region's innovation demands may be a contributing factor. Low conversion rates of research outputs, inefficient use of education funds, and a lack of cross-regional educational resource sharing all limit the synergistic effect of educational investment. In some cases, funding is diverted to administrative costs or redundant infrastructure, which limits its effectiveness in supporting innovation-driven activities. Moreover, excessive allocation to education may inadvertently crowd out other critical investments—such as enterprise R&D subsidies or technology transfer platforms—thereby weakening the overall efficiency of the innovation system. Finally, the impact of education on innovation is inherently long-term and cumulative. Given the study period (2015-2024), the data may not fully capture the delayed benefits of educational investments. In the short term, spending may focus on infrastructure and staffing, while improvements in talent quality and research capacity typically take longer to materialize. Therefore, the observed negative correlation should not be interpreted as a denial of education's foundational role, but rather as an indication of current inefficiencies in resource allocation, structural coordination, and policy integration. Moving forward, more differentiated investment strategies and mechanisms promoting integration between education and industry are needed to convert education spending into a core driver of regional collaborative innovation.

5. Conclusions and Policy Recommendations

This study investigates the structural evolution patterns of regional collaborative innovation networks and their impact on innovation efficiency, utilizing joint publication data from the Chengdu-Chongqing Urban Agglomeration between 2015 and 2024 and employing UCINET network analysis, Data Envelopment Analysis (DEA), and Tobit regression modeling. The principal findings are summarized as follows:

First, the collaborative innovation network within the Chengdu-Chongqing Urban Agglomeration has experienced rapid development, with network density increasing from 0.280 to 0.493 and average path length decreasing from 1.605 to 1.507. This evolution demonstrates a specific characteristic of networked collaborative innovation of "high density - short path - moderate agglomeration".

Second, over the 10-year observation period, the innovation efficiency of the Chengdu-Chongqing urban agglomeration exhibits a "first effective, then ineffective" trend. While pure technical efficiency (PTE) remains high in certain years, scale redundancy and resource misallocation progressively become dominant factors contributing to efficiency decline.

Third, the network structure characteristics of the Chengdu-Chongqing urban agglomeration demonstrate significant impacts on collaborative innovation efficiency. The analysis reveals that innovation efficiency shows a positive correlation with network density, while exhibiting significantly negative correlations with both network centrality potential and average path length. However, no statistically significant relationship between innovation efficiency and clustering coefficient has been identified during this ten-year period.

Based on these conclusions, the study suggests that collaborative innovation efficiency in urban agglomerations could be enhanced through improvements in several key aspects.

Firstly, the spatial structure of collaborative innovation networks should be strove to optimize. Given the positive correlation between network density and innovation efficiency, it is imperative to eliminate barriers impeding inter-regional flows of personnel and information, thereby enhancing the density of collaborative innovation networks. However, this enhancement should not prioritize connectivity breadth at the expense of quality. The establishment of differentiated synergistic mechanisms could strengthen functional division between core cities and secondary nodes, facilitating a transformation from "dual-core leadership" to "multi-polar coordination". Specifically, Chengdu and Chongqing as primary hubs should concentrate on cutting-edge technology R&D and high-end resource integration, while secondary nodes like Mianyang and Deyang could leverage their local industrial cluster advantages to deepen industry-academia-research collaboration, thereby forming complementary innovation chains. Concurrently, administrative boundary constraints on resource mobility must be addressed. Peripheral cities should be encouraged to integrate into global networks through enhanced transportation infrastructure and digital platforms, such as the construction of inter-city highways and high-speed railroads, which would enable cross-regional reorganization and hierarchical diffusion of innovation factors.

Secondly, the dynamic coordination mechanism for innovation resource allocation requires improvement. To address scale efficiency decline and potential resource redundancy in core cities, establishing a regional innovation input coordination platform is conducive to facilitate the sharing of R&D funding, talent, and equipment. As a consequence, a Chengdu-Chongqing cross-regional technology transfer center can be built to match supply and demand through market-based mechanisms, reducing duplication of inputs and idle resources. For cities exhibiting pronounced scale diseconomies (e.g., Chengdu), incremental input scale should be restrained in favor of stock optimization and technological upgrades. Conversely, for peripheral cities with greater efficiency improvement potential (e.g., Luzhou and Zigong), policy interventions should strengthen innovation carrying capacity while directing resource flows toward high-efficiency nodes.

Thirdly, the capacity for open collaboration among innovation subclusters requires further strengthening. Although the high local clustering coefficient reflects active localized cooperation, its limited contribution to efficiency indicates the presence of knowledge homogenization and collaboration barriers between subclusters. To address these challenges, the Chengdu-Chongqing Urban Agglomeration construction plan should be leveraged to promote cross-domain cooperation among subclusters, such as between Chengdu-Deyang-Mianyang and northeastern Chongqing. This could be achieved through initiatives like joint technology research and the establishment of innovation enclaves, which would introduce heterogeneous knowledge resources into the regional innovation system. Simultaneously, efforts should focus on enhancing the resilience of collaborative networks connecting universities, research institutions, and enterprises. Practical measures include forming cross-regional industry-university-research alliances, improving intellectual property sharing and benefit distribution mechanisms to reduce the costs associated with tacit knowledge transfer.

Fourthly, strengthening the long-term foundation of the regional innovation ecosystem remains imperative. Scientific research expenditures, education investments, and human capital accumulation constitute the core pillars for enhancing collaborative innovation efficiency. Particular emphasis should be placed on augmenting higher education investments in peripheral cities to expand high-quality talent reserves, while facilitating talent mobility between core and peripheral areas through innovative mechanisms such as "talent enclaves" and "flexible introduction". Concurrently, accelerating the deployment of new infrastructure—including 5G networks, industrial internet platforms, and other digital platforms—will effectively reduce temporal and spatial barriers to knowledge dissemination, thereby providing essential technological support for optimizing collaborative innovation network efficiency.

Finally, while this study provides a systematic analysis of the structural evolution and efficiency impacts of the collaborative innovation network of Chengdu-Chongqing Urban Agglomeration based on joint publications data, several limitations warrant acknowledgment. The research primarily relies on joint publication metrics, which may not fully capture the diversity of regional innovation activities as they fail to cover other multiple innovative output indicators such as patents and technology transfers. Although the 2015-2024 observation period adequately reflects short-to-medium term trends, longer-term evolution patterns still need to be tracked and verified over a longer time series. Methodologically, while social network analysis and DEA effectively characterize network topology and efficiency levels, they prove insufficient for examining nonlinear dynamic evolution mechanisms or assessing network resilience to external shocks like policy changes or economic fluctuations. Therefore, future research directions should incorporate multi-source data (including patent market transactions) to develop more comprehensive evaluation frameworks, employ dynamic network modeling techniques while tracking long-term evolution trajectories and abrupt structural changes. Moreover, policy text analysis should be integrated with spatial econometric methods to quantify impact of policy interventions on network structure and efficiency. In addition, exploring whether big data and artificial intelligence have a restructuring effect on innovation networks is also a direction worth paying attention to in the future.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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