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Towards Smart and Resilient City Networks: Assessing the Network Structure and Resilience in Chengdu–Chongqing Smart Urban Agglomeration

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Abstract: The mobility and openness of smart cities characterize them as particularly complex networks, necessitating the resilience enhancement of smart city regions from a network structure perspective. Taking the Chengdu–Chongqing urban agglomeration as a case study, this research constructs economic, information, population, and technological intercity networks based on the complex network theory and gravity model to evaluate their spatial structure and resilience over five years. The main conclusions are as follows: (1) subnetworks exhibit a 'core/periphery' structure with a significant evolution trend, particularly the metropolitan area integration degree of capital cities has significantly improved; (2) the technology network is the most resilient but was the most affected by COVID-19, while the population and information networks are the least resilient, resulting from poor hierarchy, disassortativity, and agglomeration; (3) network resilience can be improved through system optimization and node enhancement. System optimization should focus more on improving the coordinated development of population, information, and technology networks due to their low synergistic level of resilience, while node optimization should adjust strategies according to the dominance, redundancy, and network role of nodes. This study provides a reference framework to assess the resilience of smart cities, and the assessment results and enhancement strategies can provide valuable regional planning information for resilience building in smart city regions.

Keywords: city networks; complex system; resilience; smart cities; spatial structure

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1. Introduction

As a toolkit of technological services and policy interventions to address current and future urban sustainability challenges, the smart city concept has garnered significant global attention over the past few decades [1,2]. It has gradually evolved into a transformative paradigm that has redefined the trajectory of global urban development, making smart cities a new state of urban development [3]. To enhance urban competitiveness and regional efficiency, global smart city developments involve the consolidation of regional networked spatial structures to ensure an orderly flow of regional and city elements, such as population, information, knowledge, and investment [4]. Nevertheless, this consolidation can increase the vulnerability of cities in the region as a crisis event is more likely to radiate to the wider network [5]. The COVID-19 crisis exemplified how population movements between cities exacerbated the pandemic. Global climate change events are also challenging city networks [6]. Therefore, the regional structure of smart cities should be resilient to prepare for, resist, and recover from disasters, not just within the urban territory. Optimizing smart city networks for better resilience has become an urgent necessity.

For highly informative and intelligent smart cities, city-to-city connections form a network-type spatial structure under ever-compressing spatial and temporal distances, which in turn feeds back into the development of smart cities. Smart city characteristics, such as networked infrastructure, business-oriented urban development, creative activities, and the advancement of human and social capital, require the actions of inter-city networks and are influenced by their positioning in city networks [4,7]. It has been demonstrated that the source of urban system resilience is not only the elemental functions and risk environment within the city but also the city's position in the regional network and the structural performance of the network [8,9].

However, the mainstream research approach to smart cities is characterized by territoriality and locality, and its policy framework focuses more on internal characteristics without a global city perspective [10]. Local policy agendas that are uninformed about the structure of global city networks are likely to fail to attract resources such as talent, innovation, information, and business collaborations, which may affect the development trajectory of smart cities locally [7,11,12]. Therefore, the traditional research method of considering cities as independent systems is no longer applicable to smart cities, and it is particularly necessary to recognize and understand the resilience of smart cities from the perspective of complex networks.

Some scholars have already attempted to link smart and resilient cities, proposing the construction of smart, resilient cities to facilitate better mitigation of and adaptation to global climate change for sustainable urban development [6]. Existing studies have mainly treated smart cities as independent entities, exploring assessment indicators and coupling mechanisms for subsystem resilience within cities [13,14] or focusing on a single smart city governance network [15,16]. Although smart city resilience has attracted significant interest, fewer studies have examined the resilience of smart city regions from a network structure perspective [10], and there is also a lack of comparative and comprehensive analyses of networks with different attributes [17].

In the Report of the 20th Party Congress, the Chinese government made a significant national policy decision to enhance urban planning, construction, and governance, with the goal of creating livable, resilient, and smart cities. Based on this, the 'Opinions on Promoting the Construction of New Urban Infrastructure to Create Resilient Cities' was introduced on 26 November 2024, whose overall requirement is to achieve significant progress in new urban infrastructure development by 2030, with the aim of fostering the construction of a number of high-level resilient cities, thereby making urban operations in China safer, more orderly, smarter, and more efficient. China has been piloting smart cities on a large scale since 2013, and more than 300 smart city pilot cities have been officially announced, thus providing a suitable research context for this paper. Based on the above research needs, this paper chooses the Chengdu–Chongqing urban agglomeration in western China as a case study to investigate the spatial structure of multidimensional city networks and their resilience. Despite being the strongest integrated region in western China and possessing uniquely disaster-prone geographic characteristics, there has been a greater tendency to study the relatively well-developed northern Beijing–Tianjin–Hebei and coastal Guangdong–Hong Kong–Macao urban agglomerations, with little attention paid to the Chengdu–Chongqing urban agglomeration [18]. Studying its resilience, particularly in the context of smart city construction, is of great significance in promoting the security and sustainable development of this region. It will also provide valuable reference information for smart city regions in similarly non-highly developed inland areas to build resilience.

In general, the contributions of this paper are as follows: (1) the resilience of smart cities is analyzed in terms of network structure, which opens up new perspectives for the study of smart and resilient cities; (2) the spatiotemporal patterns in city networks are explored from a horizontal, multidimensional, and vertical dynamic perspective, providing more information than the study of a single static city network; and (3) the urban agglomeration in western China, which has received less attention, is selected as the study area, broadening the focus area of regional resilience research. The analytical framework, assessment results, and a series of enhancement strategies for smart city network resilience presented in this paper are of great theoretical and practical significance in enriching the existing literature on smart cities and network resilience and promoting the development of regional resilience in smart cities.

The rest of this paper is organized as follows: the next section reviews the existing literature related to smart city resilience and urban networks, followed by a presentation of the methodology. Section 4 visualizes and analyzes the study results, after which further analysis and discussion of improvement strategies are presented based on the results. This paper concludes with a conclusion.

2. Literature Review and Theoretical Framework

This section reviews smart city and city network literature to identify the tools needed to construct the multidimensional smart city network system and then reviews the methodologies and indicators needed to assess smart city complex network resilience.

2.1. Smart City Networks

Based on the flow space theory of Castells, all cities act as 'nodes' and 'hubs' to carry out the function of transmitting elements [19]. They utilize economies of scale to gain marginal returns and enhance their comprehensive competitiveness by improving their network positions to attract external resources more effectively [17]. City network formation initially relied heavily on spatial proximity, but with the rise of smart cities, information and communications technologies (ICT) are eroding the effects of geography and distance, allowing the interactive space for human economic activity to expand and urban relationships to manifest in more open network structures. Thus, the drive for digital technology innovation distinguishes smart cities from traditional cities. As studied by Khatibi et al. and de Falco et al., innovation is frequently mentioned in various smart city definitions, and it is also the key resilience characteristic that appears in almost all smart city plans [1,13]. Digital technology, as a basis for connectivity, is not only a typical representative of knowledge innovation but also the main enabler for the transfer of intangible factors, such as knowledge, to flow on a larger spatial scale [20]. Accordingly, the innovative cooperative network of digital technologies is a focal point of our research.

In the research paradigm of city networks, the world city network is inseparable from the infrastructure network, where the infrastructure system shapes the connectivity channels among cities [21]. Smart cities do not consider digital technologies in isolation but rather as connectivity tools embedded in a wider infrastructure system to meet the complex and changing needs of human beings [22]. Thus, unlike traditional cities, the infrastructure system of smart cities extends from physical space to virtual space.

Harrison et al. argue that smart cities consist of physical infrastructure, information technology (IT) infrastructure, social infrastructure, and business infrastructure interconnected to leverage the collective intelligence of the city [23]. One of the most comprehensive conceptualizations of smart cities states that smart cities are cities that utilize human and social capital, traditional transport infrastructure, and communication infrastructure in order to improve quality of life and encourage economic growth [24]. Therefore, we view smart cities as complex giant systems coupled with four major infrastructure systems (transport, communication, social, and business), where these physical (transport and communication) and non-physical (social and business) infrastructures give rise to physical (population flow) and non-physical (information flow, economic agglomeration, and technology innovation) city networks [25], as seen in Figure 1. Out of these four infrastructure systems, the transport and communication infrastructure systems carry intensive flows of people and information [20], while the social and business systems play an important role in carrying the flow of economic factors, which are related to the industrial structure and economic agglomeration of the region [5].

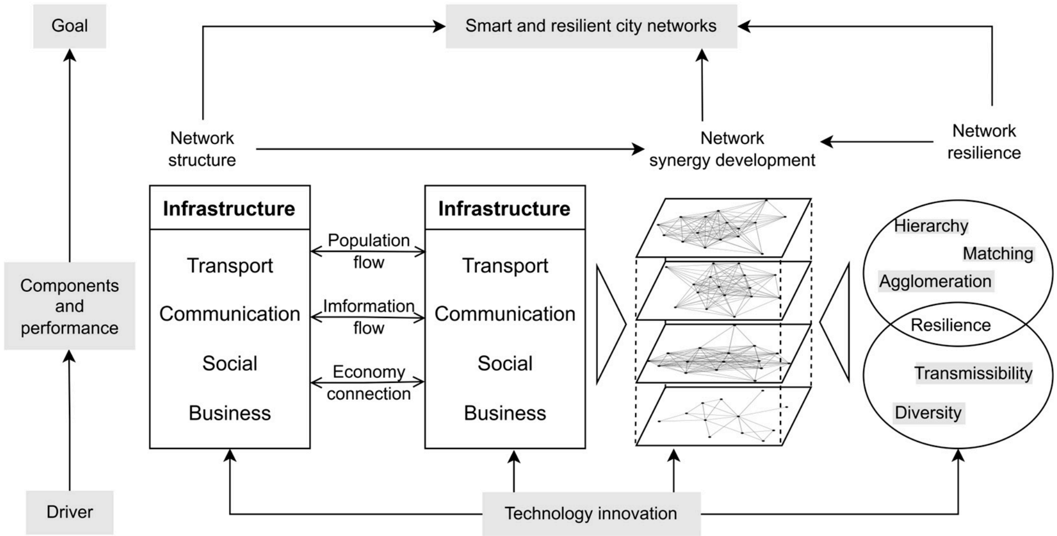

Figure 1. Theoretical research framework.

Despite recognizing that the spatial structure of intercity networks is made up of a multitude of urban nodes and multidimensional contact flows, a larger body of literature continues to favor the examination of the spatial structure of complex urban systems in terms of enterprise networks [17]. This approach originated from the study of the world city network [26], which conceptualizes the world city network at three levels: networks, nodes, and sub-nodes, where advanced producer service firms act as the agents of the city nodes. Following this, transport networks [27,28], economic networks based on city attribute data and gravity models [17,29], or knowledge/technology networks [30,31] have also made impressive achievements. However, most studies capture only one key dimension of intercity networks and lack comparative and comprehensive analyses of multidimensional networks [5,17].

Even more, there is a paucity of research on city networks within smart city regions. Palomo-Navarro and Navío-Marco use the Spanish network of smart cities as a case study to examine governance and operational models in complex networks, which provides a direction for improvement in the governance of smart city networks but neglects the focus on the network's structure itself [16]. Admittedly, research on smart city governance networks is emerging [15,32], but again, this is research on independent, single city network, and even qualitative studies rather than quantitative ones. Dynamic and multidimensional elemental endowments are important hallmarks of smart cities [25], highlighting the need for research on multidimensional element networks in smart cities. Thus, this paper contributes to deepening the study of city networks and broadening the scope of smart city research. However, it is worth proposing that because of the consideration of smart city critical infrastructures as connecting channels, the conceptual framework (Figure 1) in this paper only focuses on the economic flows, population flows, information flows, and innovative knowledge flows carried in the transportation, communication, social, and business infrastructures, and does not pay attention to the ecology or collaborative governance networks in smart cities.

2.2. Resilience Evaluation of Smart City Networks

'Resilience' is a term originally used in physics to describe the ability of a material to absorb energy and regain equilibrium after deformation. Holling applied it to measure the capacity of ecological systems, and it was subsequently introduced into urban science as a city planning strategy in the 1990s, setting off a wave of research [33,34]. Urban resilience evaluation has been emphasized as a prerequisite for urban planning decisions and resilience enhancement [8], mainly carried out through quantitative methods of composite indices [35,36] and performance curves [37,38]. In particular, geoscience and complex network methodologies are also widely used for the resilience evaluation of transport infrastructure and green space [39,40]. In general, these resilience assessments have focused on independent cities or specific city systems rather than complete complex urban network systems [8].

Some scholars are shifting their attention from conceptualization and smartness assessment to smart city resilience. Smart city planning should focus specifically on the goal of urban resilience to mitigate and adapt to global climate change [6,41]. In this regard, Canavera-Herrera et al. critically reviewed the relationship between smartness and resilience, examining the resilience content associated with smart city components of the data layer, digital technologies, and the physical city [42]. Sharifi and Allam developed a taxonomy that examined 33 smart city assessment frameworks or indicator sets in terms of alignment with resilience, which found that resilience indicators matched reasonably well with intelligence and efficiency but not as well with other important characteristics such as redundancy and diversity [43]. For the assessment of smart city resilience, Zhu et al. provided an index-based measurement method to comparatively assess the resilience of China's smart cities under infrastructure, economic, social, institutional, and environmental dimensions through a hybrid analytic hierarchy process and technique for order performance by similarity to ideal solution [14]; Khatibi et al. developed a measurement system for the smart urban water supply system resilience, which defines, from the technological dimension, the eight indicators in ICT and non-ICT aspects [13]. The promotion score matching-double difference and index methods have also been employed to measure the impact of smart city development on urban economic resilience, social resilience, ecological resilience, and infrastructural resilience [3].

Overall, smart city resilience-related research still tends to be theoretical studies [6,41,42], measurements based on index tools [13,14,43], or empirical analyses of the relationship between smartness and resilience [3,14], as opposed to an examination of the resilience of network structures. The resilience of city networks refers to the ability of city network systems to prepare, resist, recover, and adapt in the face of shocks, which extends from the definition of urban system resilience [5,44]. The fundamental properties of all resilient systems involve robustness, redundancy, intelligence, rapidity, diversity, interdependence, adaptability, collaboration, and so on [8,45]. Structure and function are the two main aspects of city network resilience, which essentially determine the various characteristics of the system resilience [44]. In terms of functionality, urban network systems place greater emphasis on the efficiency of regional cooperation and the completeness of urban functions [5]. In the theory of complex network systems, the functionality of a complex network depends heavily on structural robustness [46]. For this reason, this paper places more emphasis on the network's ability to maintain functional complementarity (redundancy) and structural stability (robustness) when measuring the structural resilience of city networks, which reflects the ability of the network system to recover, maintain, or improve its original structure and key functions [46–48].

World city network research has gradually extended the literature on city network resilience assessment, with social network analysis and disruption scenario modeling being the hotspots of application. Crespo et al. demonstrated that degree distribution and degree correlation reflecting network hierarchical and matching properties are critical statistical signatures of network resilience [49]. Subsequently, many scholars have applied them along with other commonly used topological metrics (e.g., transmissibility, diversity, connectivity, agglomeration, centrality, complexity, etc.) to assess the structural resilience of networks in ecology, population flow, economy, engineering, and more [5]. Hereby, we focus on the preventive capability of smart city networks before jamming attacks (inherent structural robustness), where hierarchy matching and agglomeration are key evaluation indicators, and the adaptive capability after jamming attacks (functional redundancy), which includes network indicators of transmissibility and diversity.

Based on the above literature review, the theoretical research framework is illustrated in Figure 1. To move towards smart and resilient city networks, we need to recognize the components of city networks within smart regions and their resilience performance before and after disturbances. Among them, digital technology innovation is the underlying driver that facilitates the flow of population, information, and economic elements carried by infrastructure in smart cities. Accordingly, we regard the smart city agglomeration as a complex system of systems composited by economic, information, population, and technology network subsystems. The synergetics of Haken posits that in a complex system, subsystems with different attributes are interrelated and constrained, and the overall effect of the system is realized through constant coordination and trade-offs [50]. Only through coordinated development among the subsystems can the complex system operate effectively and show a high level of development. Therefore, when the multidimensional smart city network structure shows sufficient resilience and develops synergistically, the composite system of the whole smart city network can achieve a high level of resilience and thus sustainable development.

3. Methodology

3.1. Study Area

The Chengdu–Chongqing urban agglomeration (see Figure 2) was selected as the study area because of its characteristics: prominent position in national strategic planning, high geographic disaster-risk environment, accelerated smart urban agglomeration construction, and polarized regional development. It has the highest population density in western China, the strongest industrial base, the strongest innovation capacity, the broadest market space, the highest degree of openness, and a unique strategic position in China's overall national development [51]. Additionally, it is in a basin and near the highly active Longmenshan Fracture Zone, making it highly susceptible to natural hazards involving earthquakes, floods, droughts, and hill fires [52]. The 2008 Wenchuan Earthquake (magnitude 8.0), the 2013 Lushan Earthquake (magnitude 7.0), and the 2022 Lushan Earthquake (magnitude 6.1) all took place here [53].

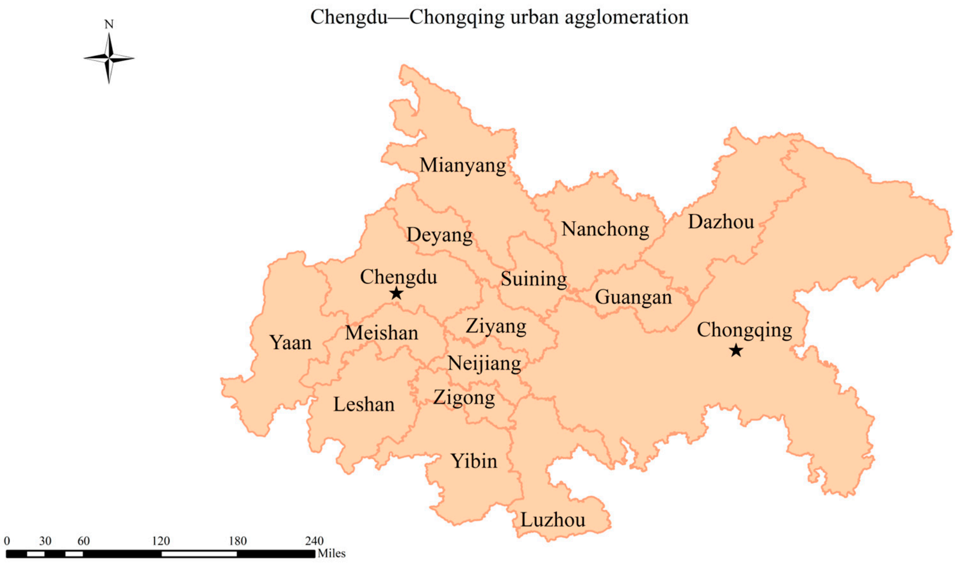

Figure 2. The study area. Note: The stars indicate the twin core cities of the Chengdu-Chongqing urban agglomeration.

The Chengdu–Chongqing urban agglomeration comprises sixteen cities, as shown in Figure 2. The national government, which launched policies in 2016 and 2021 to accelerate the pace of digital China construction and the construction of urban agglomerations, has high expectations of the Chengdu–Chongqing urban agglomeration [54]. In response, local governments across all 16 cities have released strategic plans to facilitate the construction of smart cities, gradually shaping the Chengdu–Chongqing smart urban agglomeration. Notably, ten of these cities were designated as national-level smart city pilot projects by the Chinese government between 2013 and 2015.

However, significant disparities exist in the levels of smartness among these cities due to differences in resource endowments, levels of informatization, and overall socio-economic development [14]. Smaller cities or less developed regions face challenges in achieving the same level of smart city development as more advanced areas, especially the "twin cores" of the Chengdu–Chongqing smart urban agglomeration—Chengdu and Chongqing [18]. Chengdu (the capital city of Sichuan Province) and Chongqing (a municipality directly under the central government) are the central cities driving the coordinated and synergistic development of the region [51]. Chengdu, as one of the twin cores, also developed smart city construction plans for 2020 and 2022 to promote regional integrative smart urban agglomeration construction.

3.2. Data Sources

We constructed four city network dimensions—population flows, information flows, innovation knowledge flows, and economic connections—and examined the changes in these four network structures from 2018 to 2022. Drawing on previous city network research findings and taking data availability and continuity into account, various data sources were consulted to construct the city networks (Table A1 in Appendix A).

3.3. Methods

3.3.1. Constructing the Multi-Dimensional Smart City Networks

The node and link identification approach and the associated calculation methods shown in Table A2 (see Appendix A) were used to construct the multidimensional smart city network. The economic connection network link strengths were calculated using the gravity model shown in Equation (1):

$$E_{ij} = \sqrt{P_i L_i}\sqrt{P_j L_j}/D_{ij}^b \tag{1}$$

where E_{ij} denotes the economic linkage degree between cities i and j, P_i and P_j represent the resident population in the two cities, L_i and L_j are the average night light values, and D_{ij} is the intercity geographic distance calculated from the latitude and longitude of the city center. b is the distance decreasing coefficient; if $b = 1$, the serious effect of urban distance on the city network links is avoided [29].

3.3.2. Measuring Network Correlation

After constructing the networks, this study employed the Quadratic Assignment Procedure (QAP) to analyze the correlations among the economic, information, population, and technology networks. QAP is a widely used method for evaluating correlations between multiple relational matrices [55]. By randomly permuting the rows and columns of the original network matrices (1000 iterations in this study) and recalculating correlations between the observed values and the permuted matrices, QAP generates a distribution of correlation coefficients [56,57]. Unlike traditional correlation analysis, QAP addresses the issue of non-independence inherent in network data, minimizing potential biases [58,59]. The application of QAP in this study provides insights into the interdependencies among city networks and offers a scientific basis for developing resilience enhancement strategies for the Chengdu–Chongqing urban agglomeration.

3.3.3. Measuring Network Structural Resilience

The constructed networks were then evaluated for resilience. Five network indicators were selected to characterize resilience because of their ability to reflect network robustness and redundancy. The measurements were based on social network analysis using the networkX algorithm library included in Python 3.11.5.

Hierarchy reflects the hierarchical distribution in urban systems. High-level cities are the core cities, while the low-level peripheral cities depend on the high-level cities for their development and thus are less resilient to risks [60]. Weighted degree and degree distributions (Equations (2) and (3)) measure the node properties and the overall network. While hierarchy is positively correlated with resilience, this cannot be generalized in isolation from correlation because loose bridges between the core and peripheral cities can undermine network stability [49], which is assessed using a matching indicator.

$$K_i^w = b(K_i^{w*})^a \tag{2}$$

$$\ln K_i^w = \ln b + a \ln K_i^{w*} \tag{3}$$

where K_i^w denotes the weighted degree of city i, K_i^{w*} is its degree distribution rank, and b is a constant. The degree distribution curve slope is denoted $a (a < 0)$; the larger the absolute value, the greater the network hierarchy.

Matching assesses the correlations between the connected objects and indicates the assortativity or disassortativity between city networks [8]. Degree correlation effectively measures the matching [49] and is determined using Equations (4) and (5). A network is assortative when cities are connected at the same level (positive correlation, $d > 0$); that is, the high-level nodes are connected, and the low-level nodes are connected. Conversely, a network is disassortative (negative correlation, $d < 0$) when there is high connectivity between the core city and the peripheral cities, which allows the elements to circulate smoothly across the entire network. Disassortative networks are usually highly resilient as the impact of events cannot disrupt the overall network's operational structure.

$$\overline{K_{vv,i}^{w}} = \sum_{j \in V_i} K_j^w / K_i^w \tag{4}$$

$$\overline{K_{vv,i}^{w}} = c + dK_i^w \tag{5}$$

where $\overline{K_{vv,i}^{w}}$ is the average neighborhood weighted degree, K_j^w is the weighted degree of city j which is the neighbor of city i, V_i is the set of all neighbors of i, c is a constant, and d is the degree correlation coefficient.

Agglomeration reflects the node clustering and overall network closeness and is usually measured using a node clustering coefficient and an average clustering coefficient [47] and computed using the geometric average of the subgraph edge weights (Equations (6) and (7)). A node clustering coefficient A_i is used to observe the extent to which neighbors are connected and an average clustering coefficient $\overline{A}$ indicates the overall network closeness, with higher values indicating strong network structural stability.

$$A_i = \sum_{vw} (\hat{w}_{uv}\hat{w}_{uw}\hat{w}_{vw})^{1/3} / K_i(K_i - 1) \tag{6}$$

$$\overline{A} = \sum_{i=1}^{n} A_i / n \tag{7}$$

where $\hat{w}$ is the normalized edge weight and n is the total nodes in the overall network.

Transmissibility indicates the inter-city element flow efficiencies [8]. High transmissibility means that in the face of disturbances, the exchange of information, technology, labor, and other elements between the cities is fast and inexpensive, which accelerates urban response and recovery and facilitates network reorganization and adaptation [61]. The transmissibility index, shown in Equation (8), is determined based on the global network efficiency; the larger the value, the stronger the transmissibility. The node transmissibility index connotation calculation method is similar, except that it reflects the local transmission efficiency between the measured object and other nodes.

$$T = \sum_{i \neq j \in N} \frac{1}{l_{ij}} / n(n-1) \tag{8}$$

where l_{ij} is the shortest path length between i and j, and N is the set of all network nodes.

Diversity reflects the network fault tolerance [60]. When one path between any node is subject to an external shock, to maintain a stable network structure, other paths need to ensure that the elements can flow normally through the two nodes [48]. Therefore, high diversity is a characteristic of resilient city networks. Diversity depends on the average number of independent network paths, which is determined using Equation (9). Similarly, the node diversity indicator reflects the local connectivity diversity between the measured object and other nodes; that is, connectivity paths that do not include the measured object are not considered.

$$D_i = \sum_{i \neq j \in N} p_{ij} / n(n-1) \tag{9}$$

where p_{ij} refers to the number of independent paths between i and j.

Network resilience is then determined using the maximum–minimum normalization method and the linear weighted average aggregation method.

4. Results and Analysis

4.1. Spatiotemporal Patterns in the Four Networks

Figure 3 shows the visualization results of the correlation coefficients of the four networks between 2018 and 2022. The results indicate that economic vs. information, economic vs. population, and population vs. technology exhibit significant weak correlations (approximately 0.3) from 2018 to 2022. These relationships are relatively stable over time, as evidenced by consistent significance levels. The observed correlations suggest potential interdependencies among economic connection, population flow, and information exchange within the network. Economic connections likely play a key role in driving population flow (e.g., labor migration) and information flow (e.g., information sharing in economic activities). The relevance of population and technology networks may stem from the fact that technical cooperation needs to be supported by a certain population base. For other network pairs, the correlation coefficients are generally around 0.1, with significance levels often failing to meet thresholds, which indicates that their relationships are nearly independent.

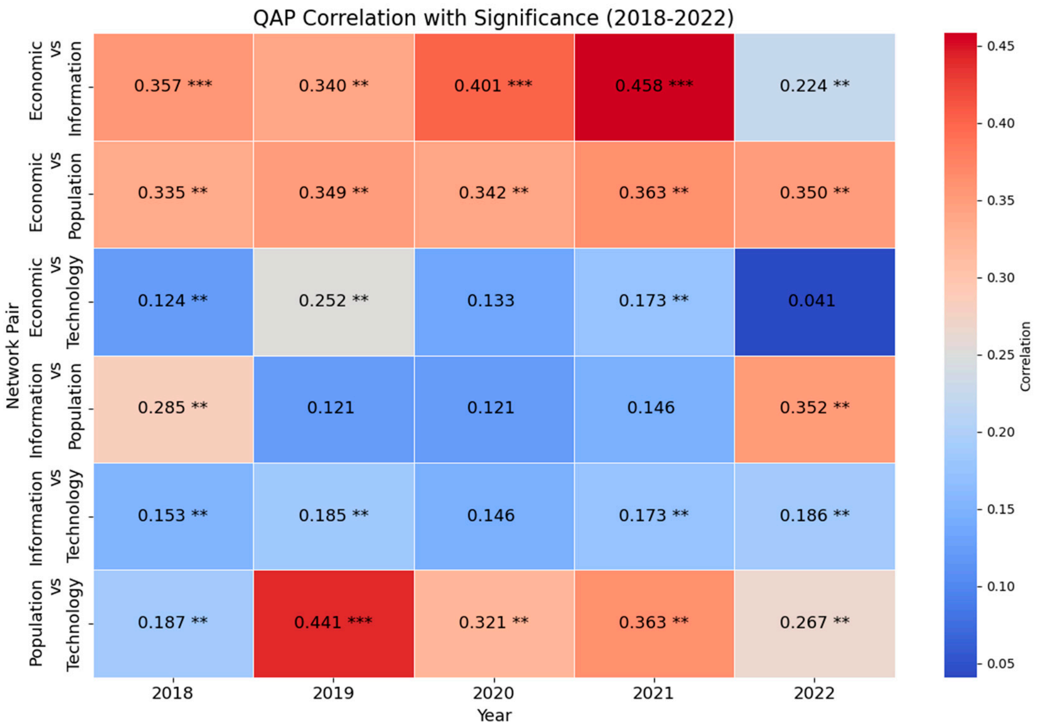

Figure 3. Heat map of correlation coefficients of multidimensional city networks. Note: *** and ** represent significance at the 1% and 5% levels, respectively.

The width of the red connecting lines in Figure 4 demonstrates the standardized connection strength between the 16 cities, enabling a comparison of the spatial patterns of the four networks. Meanwhile, Table 1 is provided to better illustrate the distribution of each network's connection strengths and their evolution over time, as it is based on the original connection values. It shows some descriptive statistics for each network type and for each year, including the mean, the standard deviation, and the minimum and maximum values.

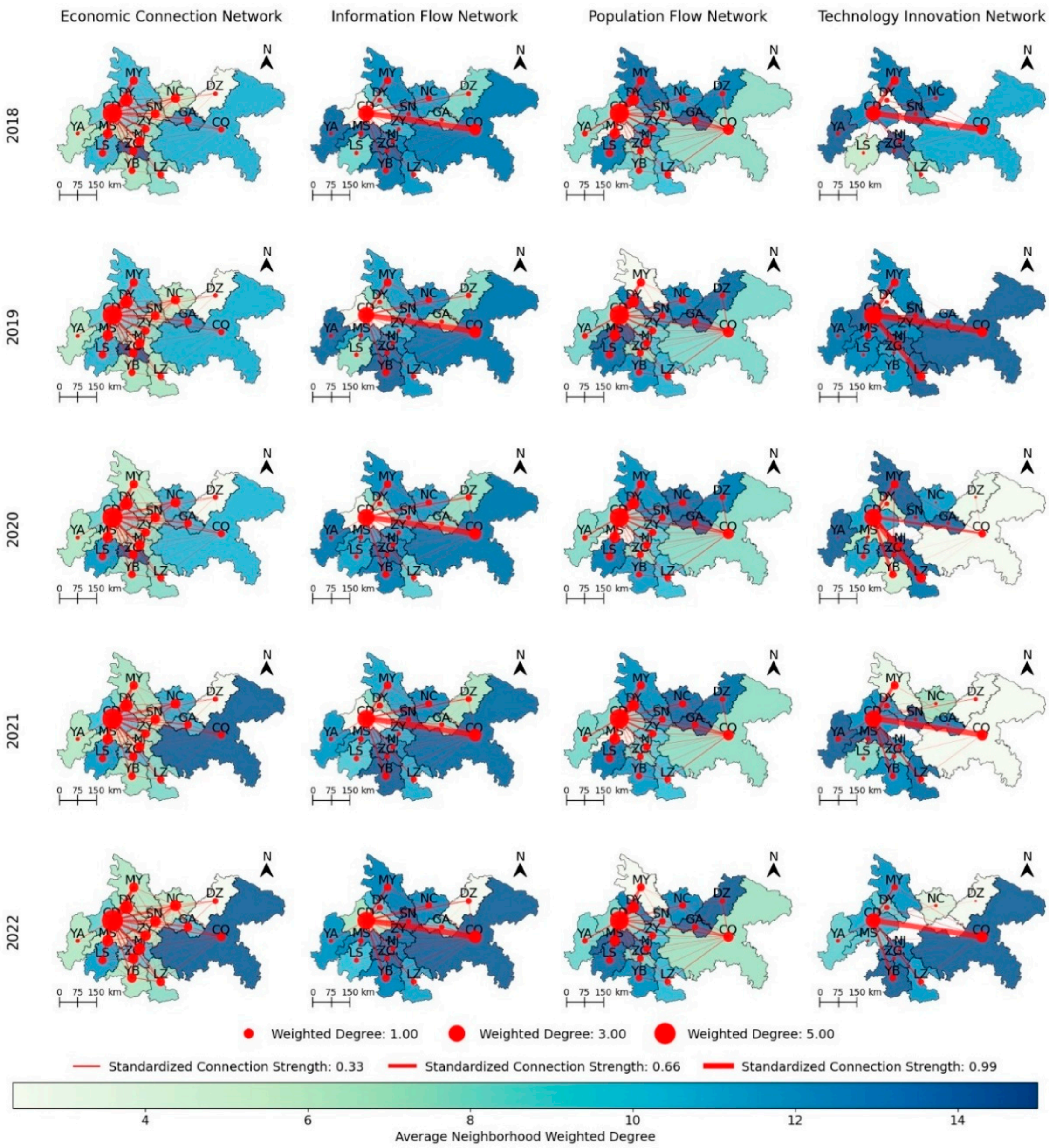

Figure 4. Weighted degree, average neighborhood weighted degree, and standardized connection strength between nodes. Note: City names are abbreviated to a combination of initials for visualization purposes. Specifically, CD: Chengdu; CQ: Chongqing; MY: Mianyang; MS: Meishan; DY: Deyang; ZY: Ziyang; NC: Nanchong; SN: Suining; GA: Guangan; NJ: Neijiang; LS: Leshan; DZ: Dazhou; YB: Yibin; LZ: Luzhou; YA: Yaan; ZG: Zigong.

Among the subnetworks, the information network is the most prominent dual-core-driven network. Chengdu and Chongqing occupy significant positions in the network with prominent weighted degrees and tight connections, while the rest are 'collapsed' peripheral areas with barriers to information flow. Nonetheless, this prominent pattern of disequilibrium is gradually weakening, as evidenced by the large year-to-year reductions in the standard deviations in Table 1. Its simultaneous large reduction in the mean also suggests that flows within the urban agglomeration are declining annually. The planning and development of smart cities have made it easier to obtain and transmit information securely. Thus, the exchange of information is no longer confined to neighboring regions but has spread from within the urban agglomeration to outside of it. In general, the information flow within the urban agglomeration is becoming weaker and more balanced.

Table 1. Data sources for the construction of the four city networks.

		Mean	Std Dev	Min	Max
Economic connection network	2018	18.37	24.56	4.95	193.62
	2019	20.69	27.36	5.49	210.63
	2020	17.76	22.26	4.65	167.73
	2021	18.93	24.13	5.15	180.68
	2022	37.92	37.25	12.54	264.95
Information flow network	2018	49,403.82	136,258.13	5549.50	1,241,877.33
	2019	39,110.67	97,366.87	4640.68	871,836.03
	2020	32,604.91	73,102.18	5191.89	649,784.70
	2021	33,497.82	68,651.51	5273.01	602,031.54
	2022	28,313.03	56,977.00	4940.00	497,361.00
Population flow network	2018	0.60	1.18	0.03	8.17
	2019	0.81	1.63	0.05	11.02
	2020	0.99	1.99	0.05	13.74
	2021	1.11	2.28	0.06	15.61
	2022	0.92	1.88	0.06	13.45
Technology innovation network	2018	15.69	26.27	1.00	97.00
	2019	21.60	34.12	1.00	118.00
	2020	12.71	19.51	1.00	83.00
	2021	12.57	19.07	1.00	83.00
	2022	12.14	22.08	1.00	101.00

The distribution of elements is relatively balanced in the economic and population networks, according to Figure 4. Influenced by geographic distance, the overall pattern shows that shorter geographic distances result in stronger economic links and population mobility. At the same time, the spatiotemporal patterns of the economic and population networks display relatively strong consistency (corroborated by the results of the QAP correlation analysis), with the networks overall showing a continued strengthening of ties and a clear trend towards centralization. Their most notable characteristic is the increasing connectivity within the Chengdu metropolitan area (Chengdu, Deyang, Meishan, and Ziyang), which is the main reason for the increase in the standard deviation of the network's connection strength.

In contrast, the overall connectivity of the technology network is weak, with a lack of cooperation between most cities. It can be seen from Figure 4 that patent cooperation exists mainly between Chengdu, Chongqing, Mianyang, Luzhou, Yibin, and Deyang, which have strong industrial bases and a concentration of scientific research institutions. Although the means in Table 1 indicate that the overall connections in the technology network are weak, the decrease in the standard deviation also implies that the connection distribution is gradually becoming more balanced. The technological lock-in between Chengdu, Chongqing, and Mianyang is gradually breaking down as the scientific and technological innovation capacity of the peripheral yet promising cities increases.

It is worth noting that, as can be seen from Table 1, there is a tendency for the connection strengths in both the economic connection network and the technology innovation network to peak in 2019 and then plummet in 2020. We argue that this may be influenced by the external environment, that is, COVID-19. Differently, the impact of the epidemic on the economy subsides, and the linkages of economic activities reach a new peak by 2022, while the technology cooperation linkages within the urban agglomeration do not show a clear recovery trend even by 2022.

4.2. Node Analysis of the Resilience Indicators

4.2.1. Hierarchy and Matching

When examining network hierarchy and matching, we obtained the weighted degree and average neighborhood weighted degree of each node, as seen in Figure 4. These two indicators permit the identification of the role and function of nodes in the network, classifying them as core hub cities (high weighted degree and high average neighborhood weighted degree), independently active cities (high weighted degree and low average neighborhood weighted degree), potential influencer cities (low weighted degree and high average neighborhood weighted degree), and peripheral cities (low weighted degree and low average neighborhood weighted degree). Table 2 illustrates the distribution of city types in each network, highlighting the diversity in city roles across different dimensions.

Table 2. Types of cities in each network based on hierarchy and matching.

	Economic Connection Network	Information Flow Network	Population Flow Network	Technology Innovation Network
Core hub cities	CD	CQ	MS, DY	CD, CQ
Independently active cities	MS, NJ, ZY, SN, NC, DY, MY, YB, LZ	CD	CD, CQ	—
Potential influencer cities	CQ, LS, ZG, GA	MY, NC, DY, SN, GA, ZY, YA, MS, NJ, ZG, LS, YB, LZ	ZY, NC, DZ, SN, GA, NJ, LS, YB, LZ	MY, YB, LZ, DY, NJ, ZG, YA
Peripheral cities	YA, DZ	DZ	MY, YA, ZG	DZ, NC, SN, GA, ZY, LS, MS

Chengdu is definitively a core hub city in the economic network, attributed to its status as one of China's largest megacities with significant economic and demographic influence. By contrast, Yaan and Dazhou are classified as peripheral cities due to their limited economic connections and stagnant growth trends. While Chongqing is also a megacity, its geographical constraints have limited its economic connections, leading to a relatively lower weighted degree. Nonetheless, Chongqing has unleashed its ability to drive and radiate in the post-epidemic era, playing the role of an influencer and steadily boosting the economy of its neighboring regions. Other potential influencer cities, such as Leshan, Zigong, and Guangan, exhibit similar characteristics. Independently active cities, including Meishan, Neijiang, and Ziyang, maintain strong economic performance but lack the broader influence of core hub cities.

The information network demonstrates the highest degree of polarization among all networks. Chengdu and Chongqing consistently hold dominant positions as the most influential cities, with the highest weighted degrees. However, their roles differ significantly. Chongqing functions as a core hub, effectively transmitting information across the network, whereas Chengdu operates as an independently active city with limited ability to diffuse its influence broadly. Most other cities, apart from Dazhou, are identified as potential influencer cities due to their bridging roles in connecting high-weighted nodes.

The population network exhibits less polarization compared to the information network. Chengdu and Chongqing are classified as independently active cities, while Deyang and Meishan have evolved into core hub cities due to the interconnected highway network between Chengdu–Deyang–Mianyang and the increased integration of the Chengdu metropolitan area. These cities not only accommodate substantial population inflows but also efficiently facilitate the movement of people across the urban agglomeration. Cities such as Ziyang, Nanchong, and Dazhou, despite their lower hierarchy, serve as strategic nodes with potential for influence transmission. Peripheral cities, including Mianyang, Yaan, and Zigong, face challenges stemming from their geographic isolation and limited transportation and business infrastructure.

The hierarchical structure of the technology network is relatively unstable. Supported by its continuously improving digital technology innovation system and rapidly growing digital economy, Chengdu serves as the core hub city of the technology innovation network. It holds a leading position in regional cooperation and has established extensive collaborative relationships with multiple cities across the urban agglomeration. Chongqing, while slightly less central than Chengdu, remains a core hub city with significant influence. Among the potential influencer cities characterized by low-weighted degrees but high neighborhood-weighted degrees, Mianyang, Luzhou, and Yibin stand out. These cities have significantly increased investments in the smart manufacturing sector in recent years and have completed numerous high-tech cooperation projects with neighboring cities, particularly Chengdu and Chongqing. Conversely, cities such as Dazhou, Nanchong, and Suining are on the periphery, facing the cooperative dilemma of seeking technological innovation resources externally due to their own weak digital technology innovation capacity.

4.2.2. Agglomeration

The node clustering coefficients of cities in the economic network show a steady upward trend, as shown in Figure 5. The groups centered on Chengdu and Yaan have become the two communities with prominent agglomeration effects in the economic network. Unlike Chengdu, Yaan has a strong agglomeration capacity but a narrow scope of agglomeration combined with the previous hierarchy analysis. The clustering characteristics of the population network remain similar to those of the economic network. It is worth noting that although cities in the Chengdu metropolitan area are hierarchically prominent, their ties are unidirectional, so the overall ties within the localized region centered on them are not tight. The clustering coefficients of the cities in the technology network fluctuate significantly. Although Chengdu and Chongqing are the core cities of the network, they do not form close cooperative teams among their directly linked partners. In contrast, Mianyang and Luzhou's clustering effects are at a high level, forming tight clusters. As for the information network, Chengdu and Chongqing have synchronized levels of hierarchy and agglomeration. They are the two major agglomeration cores, and information can be efficiently disseminated among their cluster members, while the increasing value year by year indicates that this community structure is becoming more stable.

4.2.3. Transmissibility and Diversity

The positive correlation between local transmissibility and local diversity can be observed in almost all nodes (see Figure 5), which is similar to the findings of Du et al. (2023) that transmissibility and diversity are mutually supportive. Uneven development exists in economic and population networks. Most nodes possess high levels of transmissibility and diversity, except for Yaan and Dazhou. It is difficult for them to participate in major economic activities and to obtain sufficient external linkages to buffer against economic fluctuations and external shocks. In the information network, Ziyang, Guangan, and Yaan have the lowest and decreasing values, implying that they are relatively isolated and act more as receivers or sub-transmitters of information with decreasing influence on the other cities. Almost all nodes in the technology innovation network are at a low level, suggesting that these weak cities are highly dependent on their limited connections and continue to lack extensive and diverse external connections, making it difficult for nodes to access new knowledge, technologies, or resources, further limiting their innovation potential.

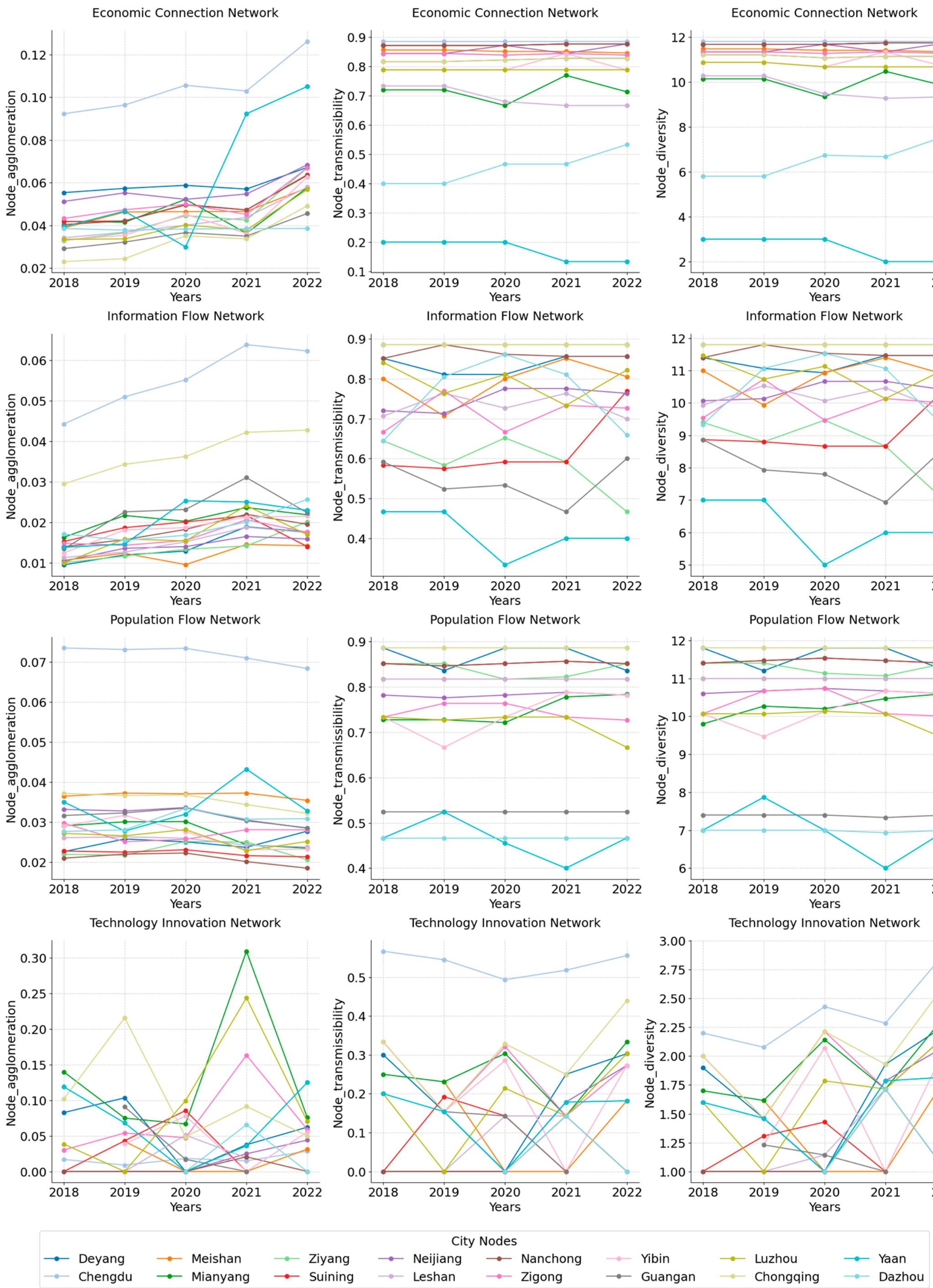

Figure 5. Agglomeration, transmissibility, and diversity of cities in the sub-networks.

4.3. Network Analysis of the Resilience Indicators

4.3.1. Hierarchy and Matching

It can be seen from Figure 6 that the matching values of all networks are negative, indicating that all four sub-networks are disassortative networks. The technology network has the highest level, where the high-level disassortativity can weaken the potential crisis of path dependence and regional locking brought by the high-level hierarchy and, therefore, is conducive to the adaptive adjustment of the network in facing shocks. The level of three-dimensionality of the network structure and the degree of diversification of path connections in the economic and population networks are relatively low, which requires further improvements in the transportation infrastructure between the core and the periphery to facilitate the flow of elements.

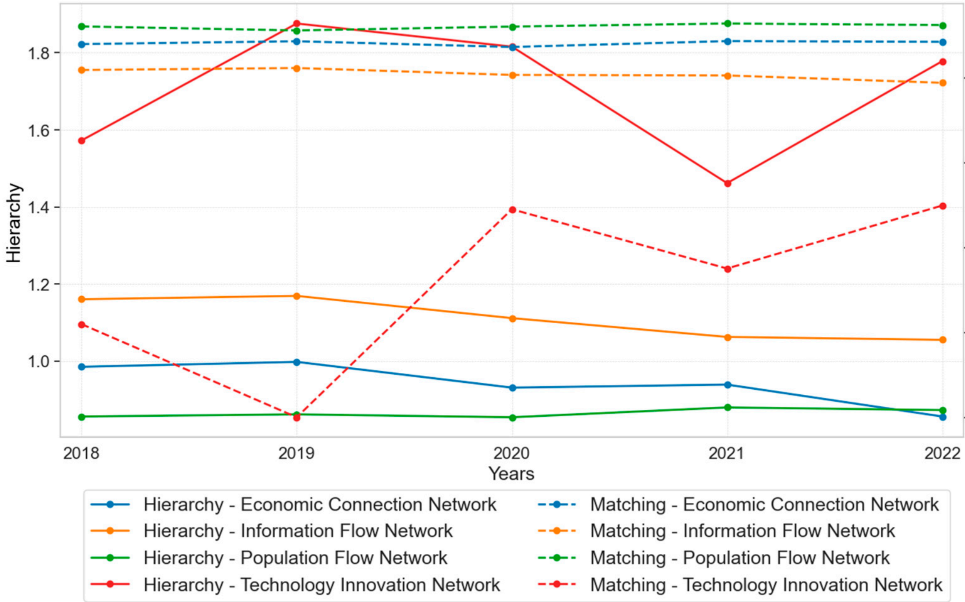

Figure 6. Changes in network hierarchy and matching.

4.3.2. Agglomeration

The agglomeration of the economic network has steadily grown over the five-year period (see Figure 7), primarily due to the roles of Chengdu and Yaan. The small triangular network centered on Yaan nestles within the larger network centered on Chengdu. Despite the high degree of global agglomeration in the technology network, there are no particularly prominent subgroups in terms of node clustering. This suggests that there are more unidirectional connections between the core and the periphery. The population network has a slightly higher level of clustering than the information network because population mobility is more strongly influenced by geographic, social, and economic factors. This leads people to form tighter clusters around Chengdu, whereas information can quickly cross geographic and social boundaries, resulting in a more decentralized network structure.

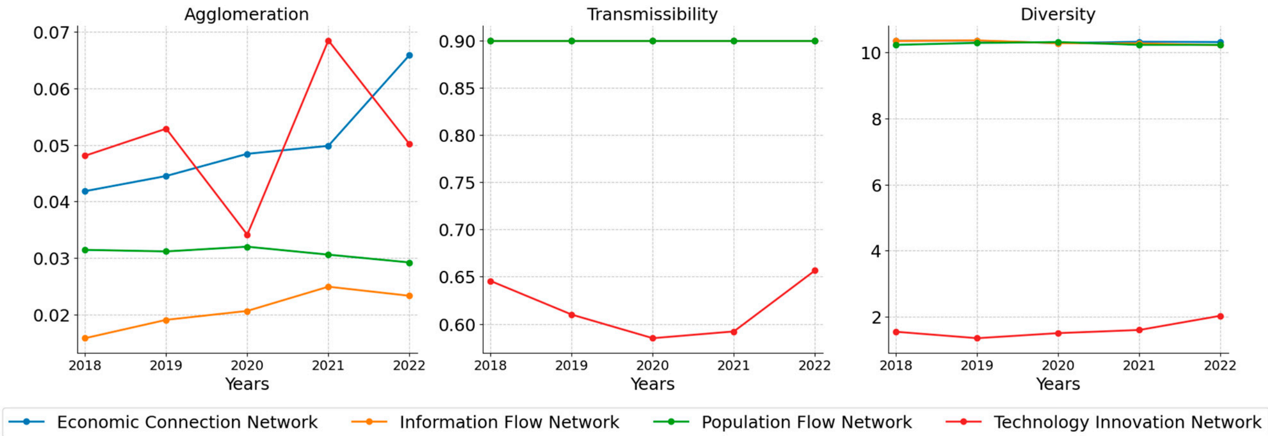

Figure 7. Networks' agglomeration, transmissibility and diversity.

4.3.3. Transmissibility and Diversity

According to Figure 7, the economic, information, and population networks all possess excellent transmissibility and diversity, indicating that elements can be distributed and transmitted between any two cities at low cost (e.g., time, distance, or other resource consumption) through multiple pathways. By contrast, the low transmissibility and diversity in technology networks suggest that information, knowledge, and resources related to digital technological innovations are difficult to circulate effectively between cities. This limitation may hinder regional innovation potential, as new ideas and innovations often originate from cross-domain collaboration. Moreover, in emergency situations (e.g., natural disasters), inefficient and monolithic technical cooperation networks hinder the rapid distribution of critical services and resources, such as disaster monitoring and smart healthcare, seriously affecting a city's ability to respond to emergencies and reconstruct after a disaster.

4.4. Integrated Characterization of Network Structures and Their Resilience

Combined with the previous analysis of the six indicators, the four types of urban nodes are connected and clustered in different ways in the four networks, resulting in the networks taking on a particular morphology, as shown in Figure 8. Although their settlement morphology and spatial evolution are different, they all show a "core/periphery" structure. The core part is mainly composed of core hub cities and independent, active cities; the peripheral part mainly consists of potential influencer cities and peripheral cities, in which the potential influencers, as the transferring intermediaries of the elements in the process of spatial evolution, have gradually increased their influence, and occasionally enter the core circle of the network.

The economic connection network has evolved from the initial 'single core + peripheral scatters' pattern to a 'multi-core community + peripheral community' pattern. Initially, Chengdu was the only core in the region, but by 2022, several independently active cities had joined the network's core circle, including Deyang, Suining, and Neijiang. They became regional economic centers within the urban agglomeration, and all established strong economic activity links with each other, which in turn formed a core community with networked connections. Simultaneously, the periphery has evolved from the original scattered pattern to a settlement pattern. Although the core and periphery are closely connected within the cluster, they are severely fragmented from each other. The economic activities of the core do not effectively radiate to the periphery, making it difficult for the cities in the periphery to keep up with the development of the core.

The information flow network is characterized by a 'multi-core community + peripheral linkage ring' and has not evolved significantly during the study period. It is a typical Chengdu–Chongqing dual-core driven network, which coincides with the positioning of the urban agglomeration. Potential influencer cities and peripheral cities are interconnected to form a locally networked peripheral linkage ring without significant agglomeration. Similarly, the shape of the population flow network has not changed significantly over the five-year period and remains broadly based on the pattern of 'multi-core community + peripheral scatters'. In contrast, the agglomeration of the population network is slightly stronger than that of the information network. Apart from Chengdu and Chongqing, the core hub cities in the population network—Meishan and Deyang—have joined the core community as population mobility centers in the urban agglomeration. There are radial connections between the core and periphery in both the information and population networks, but the peripheral parts of the population network show a scatter pattern. It can be seen that there are challenges in the population mobility between the periphery of the network. This circle-like radial spatial structure requires measures and time to develop into a more resilient networked space.

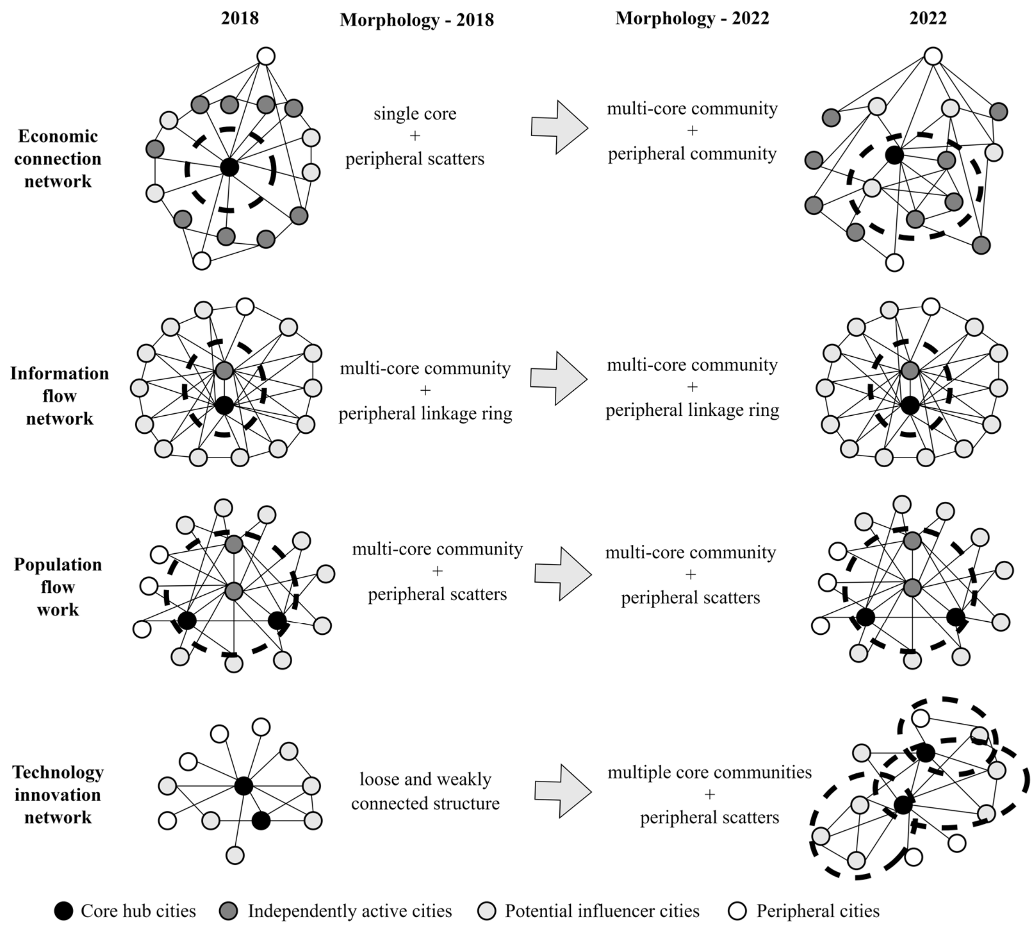

Figure 8. The morphology of the networks and their evolution. Note: we simplified the connections to capture the morphological representation of the networks, and the figure shows only the key connections between nodes with high strength. Dotted circles indicate core communities in the structure.

Regarding the technology network, its spatial morphology has evolved significantly between 2018 and 2022, from a very loose and weakly connected state to a more complex network structure, which is manifested in the form of "multiple core communities + peripheral scatters". Chengdu and Chongqing, as the core hubs of regional innovation, have a dispersive radiation-driving effect on their neighbors. By 2022, potential influencer cities such as Mianyang, Luzhou, and Deyang continue to strengthen their influence by increasing their industrial agglomeration and scientific and technological innovation capabilities. As such, they become agglomeration cores for neighboring cities, forming multiple small groups. However, the network is still in the primary stage of development, with a weak state of connection and a single form of combination.

The variation in the resilience of the network structure is shown in Figure 9. The resilience levels of all four networks are moderate, ranging roughly between 0.4 and 0.6. The technology network was the most affected by COVID-19, with its original growth trend interrupted and experiencing a sharp decline, indicating that the technology innovation network is less resistant to risk. During this period, smart city development experienced a brief stagnation. Regional blockades limited the mobility of talent and knowledge exchange, while cities reallocated their resources and attention, spending more on epidemic response than on smart manufacturing and IT infrastructure-related technological innovation activities. As a result, small groups in the network that were originally tightly connected were broken up, and reduced agglomeration decreased the network's resilience. Fortunately, the network demonstrated a certain degree of ability to recover and reorganize. After the epidemic, resilience gradually improved, but it did not return to its pre-event state, let alone build back better. This suggests that recovery efforts were focused on short-term responses rather than long-term structural improvement. The urban technology network did not use the crisis as an opportunity for transformation and upgrading.

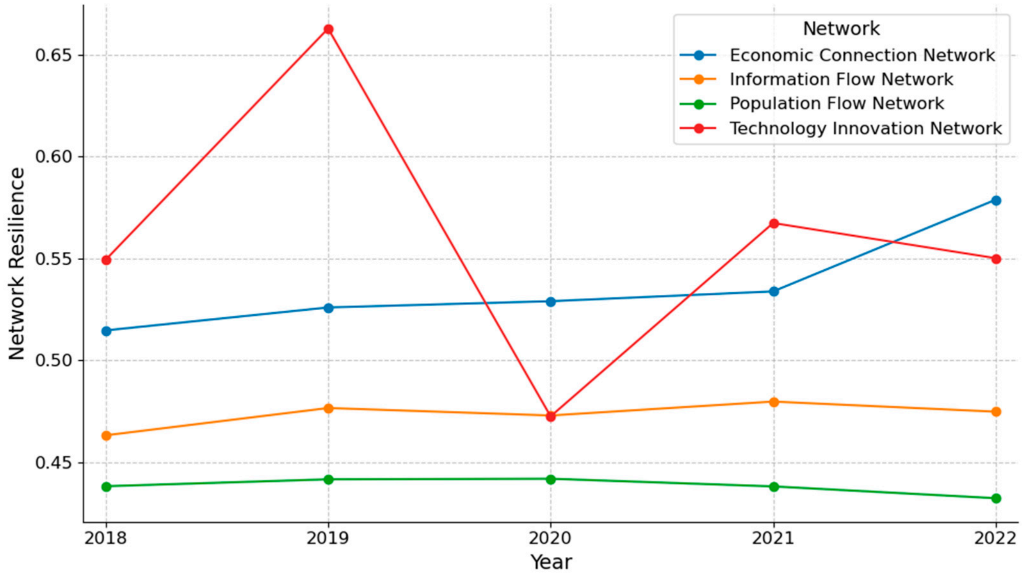

Figure 9. Resilience of four networks.

The resilience of the economic network was not significantly affected by COVID-19 and has even risen steadily since then. The evolution towards a multi-center structure supports the increase in network resilience, as it enhances the adaptability of cities while diversifying external risks. Cities can be more flexible in adjusting their strategies and resource allocations to their own and their neighbors' circumstances, and this adaptability makes the network more stable in the face of change and uncertainty. Additionally, communication infrastructure, smart healthcare systems, smart logistics, smart financial services, and data-driven urban decision-making all contribute to mitigating the impact of epidemic shocks on the economy [62].

Information and population flow networks exhibit relatively low levels of resilience due to poor structural steepness, disassortativity, and agglomeration characteristics despite being functionally strong in transmission efficiency and fault tolerance. Surprisingly, they show stability against COVID-19 shocks, implying that transmissibility and diversity are key to coping with external shocks, consistent with [63]. Consequently, economic, information, and population networks are stable even in the face of COVID-19, whereas the technology network shows great instability and vulnerability. However, the long-term stability of information and population networks may also suggest structural rigidity and a lack of necessary adaptability and resilience. A rigid network structure may struggle to effectively adjust and respond to other types of external shocks in the future, such as natural disasters and economic fluctuations, thereby increasing the overall vulnerability of urban agglomerations.

5. Discussion

This section further discusses the major networks and nodes in smart city networks, exploring how to develop targeted resilience enhancement strategies based on the above assessment results. Major networks and nodes are identified by considering both the synergistic level of network resilience and node disruption scenarios. The applicability and generalizability of the enhancement framework are also discussed to further confirm the research implications.

5.1. Major Networks in Terms of Their Synergistic Degree

For the purpose of identifying major networks, we calculated the synergistic degree of the pairwise subsystems and the total composite system over a five-year period, referring to the synergy model of Wu and Qiao et al. [64,65]. The calculation process and results are shown in Appendix B and Figure 10. The existence of low synergy networks is detrimental to the construction and development of the overall resilience of smart city regions; thus, they are considered key targets for improvement.

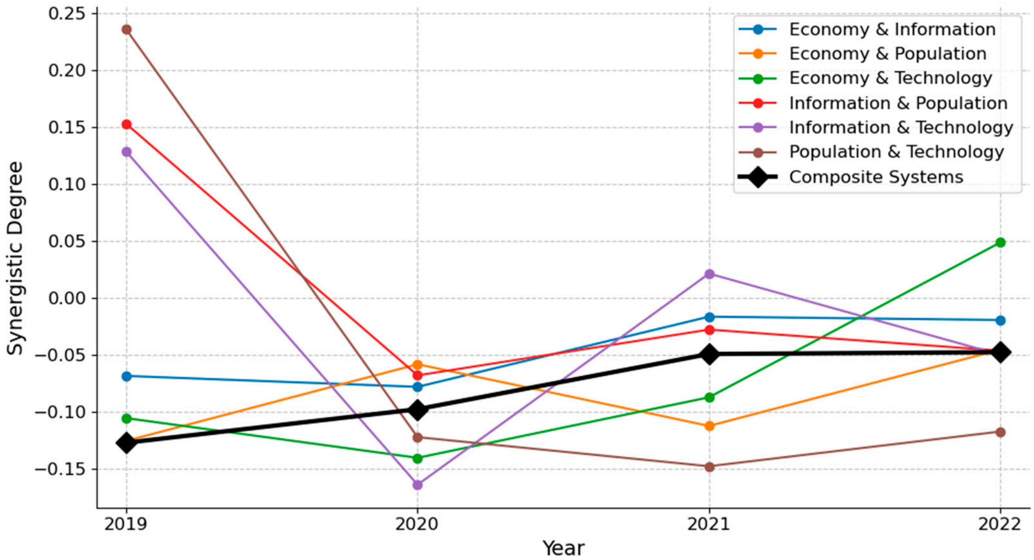

Figure 10. Synergistic degree of systems.

The negative synergy of the composite systems in Figure 10 indicates low synergy in the resilience of the economy, information, population, and technology networks and that interactions between the networks have led to a '1 + 1 < 2' outcome.

The synergistic degree of 'Economy & Information', 'Economy & Technology', and 'Economy & Population' follows the same trend as the composite system, e.g., the situation gradually improves amidst fluctuations. In 2022, the resilience of the economy and technology networks achieved initial synchronization. The technology innovation cooperation network accelerates the development and application of technology by facilitating knowledge-sharing and research cooperation, which stimulates economic activity and promotes economic network development. The strengthened economic connection networks then provide market and financial support for technological innovation, promote the commercialization and widespread application of digital technologies, and further contribute to smart city development.

However, the synergistic degree of 'Population & Technology', 'Information & Population', and 'Information & Technology' fluctuates frequently and decreases significantly, especially the population and technology networks, which have fallen considerably behind the other coupled systems in 2022 and thus are the main culprits of the low synergy of the composite system. In the future, more efforts should be focused on the synergistic development of the resilience of population, information, and technology networks.

5.2. Major Nodes in Multi-Dimensional Networks

We analyzed major nodes through disruption simulation, recognizing that not all city nodes can fail simultaneously. Given the unique geographical location of the Chengdu–

Chongqing urban agglomeration, which is highly susceptible to natural hazards such as earthquakes, floods, and droughts, we simulated the impact of these stochastic events on the structural resilience of the networks by removing single nodes. Node failure affects network performance in hierarchy, matching, agglomeration, transmissibility, and diversity by disrupting connections within the network, which in turn affects resilience. The results, shown in Figures 11 and 12, identify dominant and redundant nodes. Dominant nodes (e.g., Chongqing in the information network) possess prominent negative externalities; their failure disrupts the entire network, reducing efficiency and alternative paths, and therefore are unable to maintain network resilience when subjected to shocks. In contrast, the failure of redundant nodes provides an opportunity to optimize resilience through reallocation of resources or restructuring. For instance, the failure of Chengdu or Yaan in the economic network reduces the concentration of resources within the urban agglomeration, allowing other cities to develop, thus enhancing overall resilience. Different types of nodes require different improvement strategies, which are discussed in detail in Section 5.3.

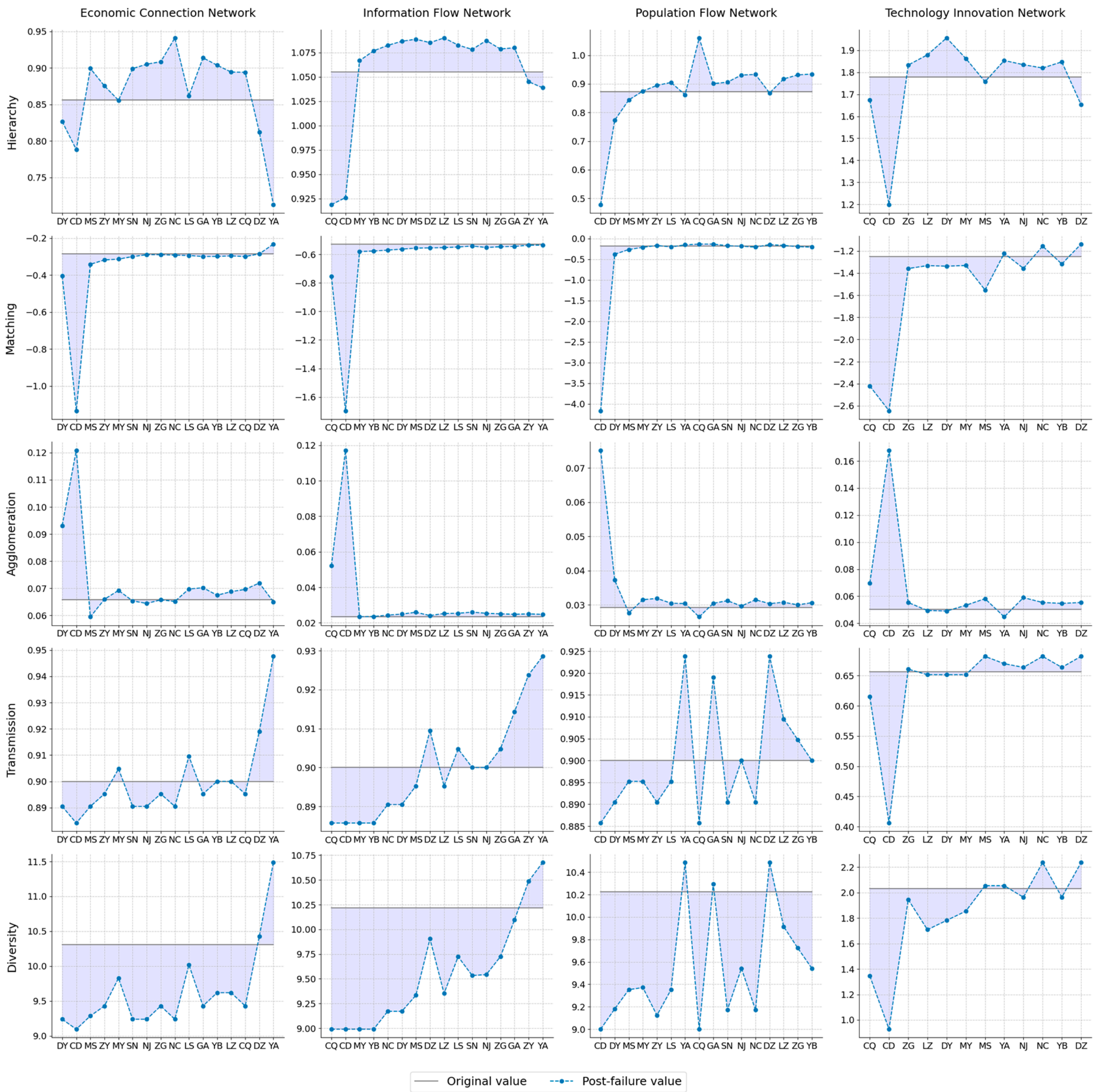

Figure 11. Network resilience indicators after node failure.

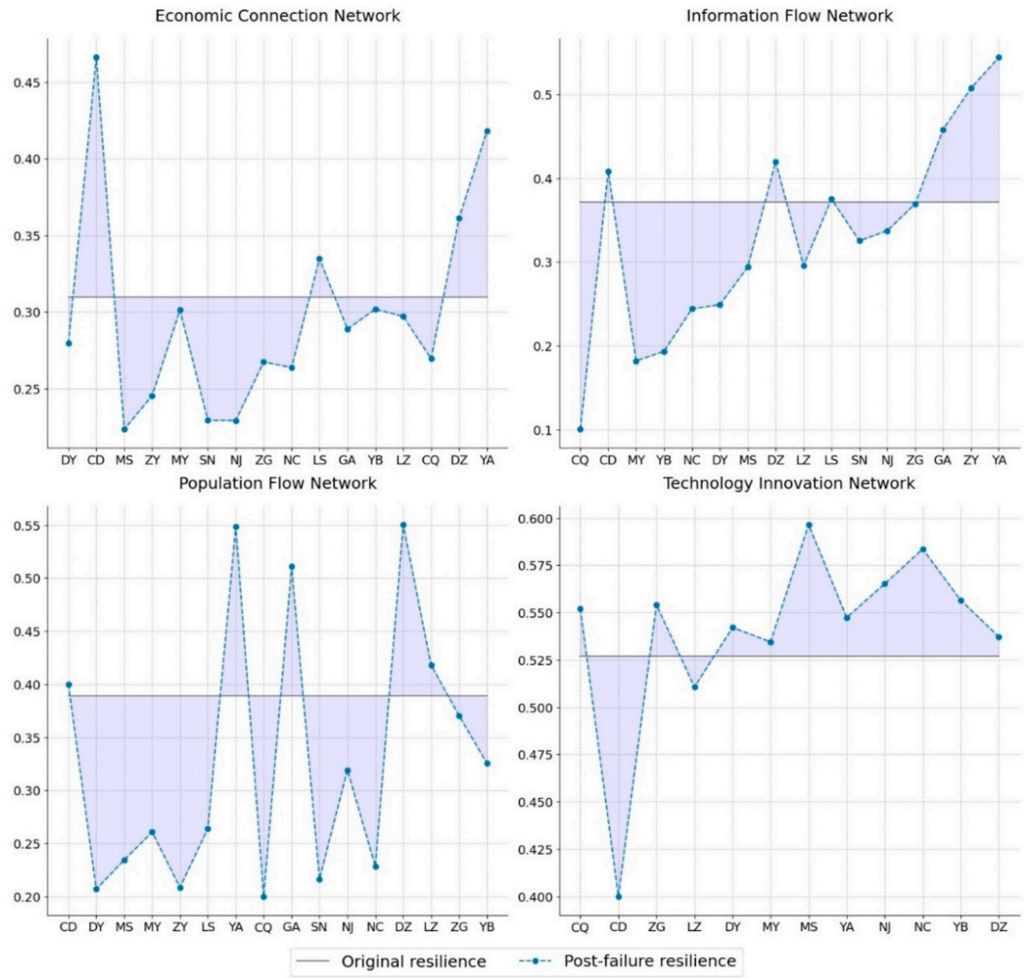

Figure 12. Network resilience after node failure.

As shown in Figure 12, disruptions to most cities in economic, information, and demographic networks result in reduced network resilience. These dominant nodes tend to be core hub cities, independently active cities, or potential influencer cities with high centrality or influence. Node failures have stronger negative externalities in the information and population networks than in the economy and technology networks. The failure of certain dominant nodes can cause more than a 40% loss in network resilience, such as Chongqing, Mianyang, and Yibin in the information network and Chongqing, Deyang, and Ziyang in the population network. This may be due to the fact that both information and population networks are highly interconnected, and these nodes are key connectors; thus, their failure seriously affects the transmission efficiency and alternate paths of information and population flows within the networks. The dominance of nodes in the economic network is not obvious. Although Meishan, Suining and Neijiang are in a relatively dominant position, their failure would not cause a significant reduction in network resilience. They are all independently active cities in the network, and the nodes they connect to are neighborhood cities at a low hierarchical level. However, they are important nodes connecting edge cities, so it can be observed from Figure 11 that their failure will have a more prominent negative impact on network transmissibility and diversity.

By contrast, Chengdu and Luzhou are only typically dominant nodes in the technology network (see Figure 12). Their failures do not have similar pathways of action on the technology network. Chengdu is the absolute leading core hub city in the network, and its failure will negatively affect the network hierarchy, matching, transmission and diversity at the same time. In contrast, in Luzhou, as a potential influencer city, failure mainly affects the network resilience by interrupting the independent paths among the rest of the nodes. There are many redundant cities in the technology network whose failure optimizes network resilience due to the high concentration of important nodes and the large number of peripheral cities in a weakly connected state, resulting in a highly redundant network structure. Chengdu and Yaan are redundant cities in the economic network even though they are the two main agglomeration cores. The reason for this is that failure can weaken the fragmentation between the core and the periphery and enhance overall network resilience. The redundant nodes in the information and population networks largely overlap; Yaan, Ziyang, and Guangan are in the information network, and Yaan, Guangan, and Dazhou are in the population network. They are all potential influencer cities or edge cities with a low level of hierarchy, so their failures are highly effective in reducing redundant paths in the network and improving transmission efficiency, as seen in Figure 11.

5.3. Resilience Enhancement Strategies for Smart City Networks

Aiming to comprehensively and systematically improve the resilience of smart city networks, we designed the resilience improvement framework shown in Figure 13. The framework considers both node improvement and system optimization, leveraging characteristics of smart cities such as a high degree of digitization, openness, data-driven decision-making, and advanced infrastructure systems. System optimization starts with actions from a composite system perspective, focusing on the positive synergies and interactions of the flow elements of economy, population, information, and technology. At the same time, for the subsystems that significantly impact the overall synergistic effect, it is necessary to promote their orderly nature, ensuring steady resilience growth. Subsystem optimization is implemented with the assistance of node improvement, focusing mainly on dominant and redundant nodes that affect the resilience of the subnetwork. Implementing these strategies in complex smart city networks can pose significant political and economic challenges, and for this reason, we also emphasize the importance of coordinating the demands of different sectors and stakeholders in the framework, as well as fostering citizen participation in governance [66,67].

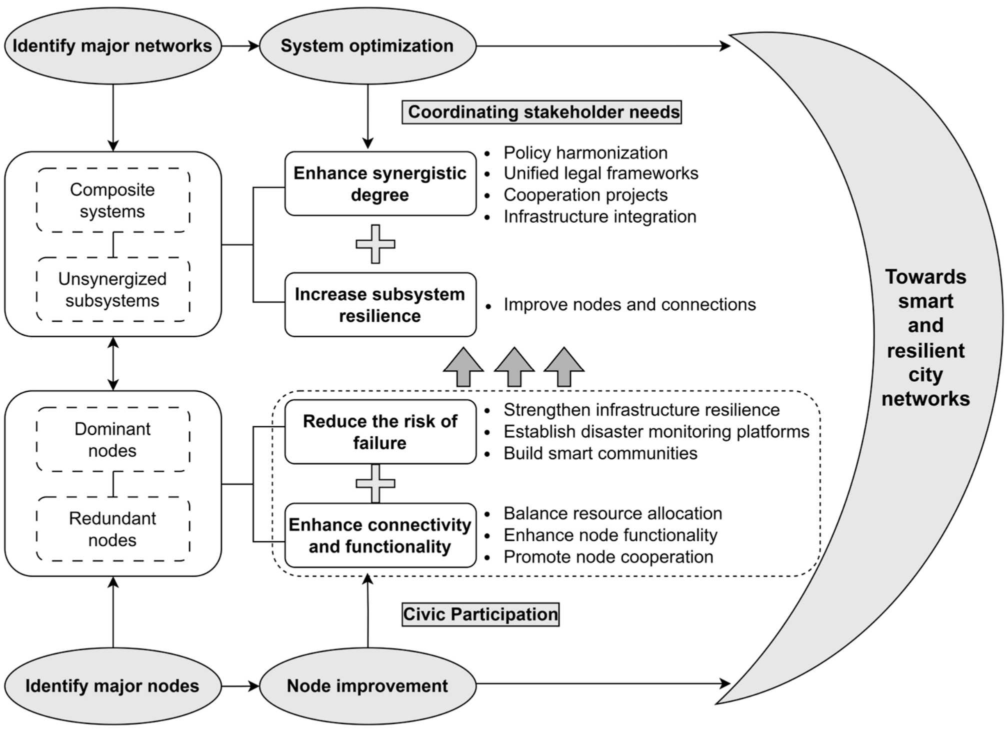

Figure 13. The resilience improvement framework for smart city networks.

Improving the synergistic degree of the composite system necessitates adjusting and optimizing policies to ensure coordination in economic development, population management, information technology, and technological innovation, thereby reducing conflicts between policies and inefficient resource allocation. Specific strategies include policy harmonization, unified legal frameworks, collaborative projects, and infrastructure integration. Cross-sectoral coordination committees or task forces comprising representatives from different cities, industries, and academic institutions should be established should be established to align priorities and improve policy integration [68]. A responsive legal framework is necessary to ensure policy coherence across regions. This includes harmonizing environmental, economic, and social policies to reduce jurisdictional conflicts [69]. Collaborative projects, such as shared data platforms and cross-disciplinary research, can further enhance integration. At this point, open data laws should be used to support shared data platforms across cities to ensure transparency in policy implementation and enhance trust among residents [67]. Policies that promote data interoperability, such as the European Union's General Data Protection Regulation (GDPR), can serve as models for fostering trust while ensuring privacy [70]. Efficient and secure connectivity of infrastructures across industries and sectors facilitates the effective flow of data and other production factors. But, infrastructure integration presupposes the promotion of public–private partnerships because involving private actors in the design and implementation of smart infrastructure projects can help address the political challenges that inter-city collaboration will face [68].

Strengthening subsystem resilience requires targeted development strategies for dominant and redundant nodes. Special consideration should be given to the hierarchical and matching positions of these nodes within the network to devise more precise and effective strategies. Both dominant and redundant nodes can be found across all four city types: core hubs, independently active cities, potential influencer cities, and peripheral cities. Dominant nodes are rarely peripheral cities; instead, they are typically located in regions characterized by high centrality or significant influence. Therefore, for dominant cities that have a devastating impact on network resilience, it is essential to minimize their risk of failure.

First, to enhance the ability of city networks to cope with and recover from all kinds of shocks and improve reliability, durability, and self-repair abilities, urban infrastructure resilience needs to be enhanced, such as upgrading smart transportation, smart logistics, smart grid, and smart finance systems [71]. Specifically, the full potential of IoT in transportation and grid management can be realized. By predicting traffic conditions, IoT can help reduce road congestion and accidents by creating new roads, directing vehicles to alternative roads, collecting and providing information on parking lots, and enhancing transportation infrastructure based on congestion data [72]. Deploying smart metering facilities in the grid, including sensors installed at customer access points and on production, transmission, and distribution systems, can help improve the efficiency, reliability, and sustainability of electricity production and distribution [73]. Of course, to achieve resilience and justice, infrastructure should not be limited to smart physical infrastructure; it should also take into account the social, economic, and knowledge dimensions. The case study of Tehran by Alizadeh and Sharifi confirms this [71]. Resilient infrastructure in smart cities must also be inclusive and is only effective if it provides equitable access to all social groups [14]. Second, to reduce disaster risks in cities, big data systems need to be interrogated to develop efficient disaster monitoring and emergency response platforms, much like the São Paulo state did in its response to COVID-19 [74]. The third is to implement smart community initiatives, where the deployment of IoT systems in disaster management, health care and public safety can empower local communities and contribute to rebuilding resilience [75].

In contrast, redundant nodes are predominantly peripheral cities, though they may also be distributed among other city types. For redundant cities, strategies to improve network resilience should focus on enhancing their connectivity and functionality, thus improving the stability and effectiveness of the entire network. This involves balancing resource allocation, enhancing node functionality, and promoting cooperation among nodes. Considering that redundant nodes in different networks may be low-level peripheral cities or potentially influencers, high-level but low-influence independent, active cities, or high-level and high-influence core hub cities, specific strategies will also have to be focused on each of them. For example, for redundant cities that are core hubs, more effort should be put into directing resource outflows and balancing regional development; independently active cities need to strengthen their influence by promoting connectivity, and peripheral cities need to be considered for both of these strategies, as strengthening functionality and connectivity are equally important to them. Detailed strategies need to be realized by considering different networks, as redundant nodes have unique functions and positioning in each network.

The main redundant technology and population network nodes are all peripheral cities in the Chengdu–Chongqing urban agglomeration. The main redundant technology, information, and population network nodes are peripheral cities or potential influencer cities in the Chengdu–Chongqing urban agglomeration at a low hierarchical level, which implies that improving the functioning of the node areas is an important direction. Therefore, targeted technology support policies are needed in these cities, such as tax incentives, providing funding, and service support [76]. Enterprises and organizations should be encouraged through tax incentives to use the crisis as an opportunity for transformation and upgrading, exploring new technologies and business models to enhance the network's ability to recover from and learn from the crisis. Further to this, peripheral cities can address financial constraints through innovative financing mechanisms. For example, integrating smart city projects into broader development plans can attract investment from international development banks or climate funds [77]. External collaborations and international partnerships can introduce resources, expertise, and innovative practices, further strengthening the region's resilience [78]. Leveraging frameworks like the European Union's Digital Europe Program could inform technological and governance frameworks.

Regarding redundant nodes in the low-resilience population network, first, peripheral city competitiveness should be increased using economic incentives and transportation infrastructure optimization. Second, migration and population mobility policies should address residents' concerns about quality of life by improving the population mobility support system, including affordable housing, employment services, social integration, education, and healthcare. Third, these cities should be encouraged to develop special tourism and cultural attractions [79]. The resilience of the population flow network will be greatly facilitated by guiding the rational distribution of the population and reducing the overdependence of redundant cities on dominant cities [80].

Some of the peripheral cities, potential influencer cities, and independently active cities exhibit redundancy in the information network. Moreover, low information network resilience is mainly because of low agglomeration, so strengthening the connectivity between redundant and core cities may be crucial. Sharing and utilizing information can be facilitated by encouraging governments and businesses to provide greater data access to increase the transparency and availability of data. Platforms for inter-city information exchange and collaboration can also be developed, such as shared databases, online forums, and collaboration tools, to facilitate more effective knowledge and information flows between the cities [81]. These collaborative information platforms must integrate residents as contributors and beneficiaries, ensuring that information networks evolve to reflect local preferences.

Redundant cities are prominently featured in the economic network, involving core hub cities and peripheral cities. The centrality of Chengdu in the economic network results in resource concentration, creating redundancy and potentially limiting the economic growth of other cities. Therefore, achieving a more equitable distribution of economic resources is essential for enhancing the overall resilience and efficiency of the economic network. The government should particularly support Yaan's economic diversification and its economic, technological, and human resource cooperation with cities outside Chengdu to share development opportunities. Concretely, interventions could include financial incentives, such as tax relief and grants, to attract investments in industries where Yaan has comparative advantages, such as eco-tourism, green energy, and sustainable agriculture [82]. Additionally, initiatives such as joint research projects, industrial collaborations, and talent exchange programs can bridge gaps in innovation and skills, enabling Yaan to participate more actively in the region's economic activities. To facilitate this process, regional planning authorities should invest in infrastructure projects that enhance connectivity between Yaan and its neighboring cities. Improved transportation networks, digital infrastructure, and logistics systems can reduce transaction costs, increase trade, and create a more integrated economic space. The study by Netirith and Ji used data envelopment analysis to confirm that improving logistics nodes and transportation connectivity through investment in infrastructure can promote regional integration and trade growth [83].

The Chengdu–Chongqing urban agglomeration is an open system that operates within a broader network of cities and regional systems in China and other countries. This is why we have emphasized the importance of international cooperation and investment in the discussion above. Meanwhile, the connectivity of the Chengdu–Chongqing urban agglomeration with China's major urban systems, such as the Yangtze River Delta, the Pearl River Delta, and Beijing–Tianjin–Hebei, will also help to increase the resilience of technology, information, population, and economic networks [84]. For example, collaborative research projects between Chengdu and Chongqing and leading technology centers such as Shenzhen and Beijing can facilitate the sharing of expertise and resources in areas such as artificial intelligence and 5G development. Such interactions will strengthen the technology network and innovation capacity of the urban agglomeration. At the same time, the city's population attraction policies facilitate the inflow of skilled labor within the network system and even from other regions, which will also create opportunities for knowledge transfer and information exchange [85]. The Chengdu–Chongqing urban agglomeration should particularly strengthen its economic and trade ties with the Yangtze River Economic Belt, as such external links can provide markets for local industries and supply chains and enable cities within the urban agglomeration to gain access to advanced manufacturing and financial resources from the coastal region [84].

The open-system perspective also highlights potential challenges. For instance, heavy reliance on external economic inputs could expose the region to global economic shocks, such as supply chain disruptions during the COVID-19 pandemic [86]. Similarly, discrepancies in governance frameworks between Chengdu–Chongqing and its international counterparts may hinder the implementation of collaborative projects. To address these issues, coordinated policies and flexible governance structures are essential.

5.4. Research Implications

On the basis of previous research on city network resilience, this paper constructs economic, information, population, and technology networks for smart city regions, where the network construction method is mainly drawn from the research of Du et al. [5]. We both constructed multidimensional networks and assessed network resilience using topological metrics, but there are some significant differences in terms of the research object, research context, and research content. First, this paper addresses smart city networks, so the network construction pathway was improved by combining the digital economy pattern, the system openness, and other characteristics of smart cities. For example, the technology network especially adopts patent cooperation data related to the digital economy, and more comprehensive and objective nighttime lighting data rather than GDP are used to construct the economic connection network. Moreover, this paper does not target a specific COVID-19 context; instead, we use node failure simulation to comprehensively model the impact of various types of stochastic events on network resilience. On top of that, in contrast to Du et al.'s analysis that focuses on local cities, our research component emphasizes the importance of cross-network synergy as well as simultaneous network optimization and node improvement.

Overall, this study makes valuable theoretical and practical contributions to assessing and improving the intercity network resilience of smart cities. The theoretical research framework and analytical methods for smart city network resilience can be replicated and generalized to other smart regions, and the practical strategies for enhancing network resilience can provide useful insights for practitioners related to urban planning. However, the case study may limit the generalizability of the findings and enhancement strategies while validating the framework. Hence, we further discuss here how the proposed resilience improvement framework can be applicable to other smart regions.

This proposed framework for network resilience enhancement is grounded in the Chengdu–Chongqing smart urban agglomeration, which is an important inland region for China's national strategy. It possesses regional characteristics such as a high geographic disaster risk environment, polarized regional growth, and rapid smart city development, which make it a representative region for studying smart city networks in inland areas of emerging economies and developing a unique pattern of resilience enhancement. For instance, the region's vulnerability to natural disasters necessitates high attention to the preparedness and resistance of the dominant nodes. In addition, the extreme differences between core and peripheral cities require targeted strategies to promote balanced development. Therefore, such a resilience improvement framework for smart city networks is generally applicable to address the resilience challenges of other smart regions with similar characteristics and, in particular, can inform the smart urban agglomerations of non-highly developed inland regions that are being built at an accelerated pace.

Nonetheless, the strategies proposed can be adapted to other regions by taking into account the varying degrees of resource endowment, governance capacity, and socio-economic development in other regions. For example, smaller urban agglomerations or low-income regions often face limited resource availability and governance capacity. Here, customized strategies that prioritize equitable resource allocation, governance structure strengthening, and international partnerships may be critical [87]. Smaller urban agglomerations could first benefit from focusing on strengthening basic infrastructure and enhancing basic connectivity before addressing high-level issues such as innovation capacity. Beyond that, urban agglomerations in less developed or low-income areas could adapt the proposed framework by emphasizing low-cost, high-efficiency strategies. Priority should be given to addressing fundamental gaps in access to resources and improving governance capacity [88]. Specifically, international assistance and partnerships can play an important role in providing the technical and financial support needed to implement smart city solutions [89]. In addition, the promotion of community-based innovation can enable local residents to actively participate in the design and implementation of smart solutions, ensuring their sustainability and cultural relevance [90].

6. Conclusions

This paper examines the Chengdu–Chongqing urban agglomeration, constructing an intercity network of smart cities from the dimensions of economic connection, information flow, population flow, and digital technological innovation. It analyzes the dynamics of network structure and resilience between 2018 and 2022. Based on the results of the analysis, targeted and comprehensive strategies are proposed for policymakers to facilitate the development of smart and resilient city networks. The main conclusions are as follows:

(1) The economy–information, economy–population, and population–technology network pairs exhibited stable and significant weak correlations over the study period, suggesting potential interdependence between economic linkages, population mobility, and information exchange within the networks. Clear trends are observed in the evolution of spatial patterns across the four networks. Economic and population networks show a continued strengthening of linkages and a noticeable concentration trend, particularly the integration degree of the Chengdu metropolitan area, which is gradually increasing. The information network is the most typical dual-core-driven network, but its internal flow is gradually shifting outside the network. The connection strength of the technology network is weakening, but the distribution of connections is gradually becoming more balanced.

(2) All networks display a 'core/periphery' structure. The economic network has shifted from a 'single core + peripheral scatters' mode to a 'multi-core community + peripheral community' mode, while the population flow network remains an unchanged 'multi-core community + peripheral scatters' pattern. The information network is characterized by a 'multi-core community + peripheral linkage ring', while the technology network has evolved from a loosely connected state to a 'multiple core communities + peripheral scatters' structure.

(3) The function and positioning of nodes in the network can be identified based on their performance in weighted degree and neighborhood weighted degree, classifying them as core hub cities, independent active cities, potential influencer cities, and peripheral cities. The development of resilience enhancement strategies should take into account these urban roles in each network. Local policies related to strengthening the functioning of nodes, promoting node cooperation, and balancing resource allocation are applicable to different city types.

(4) Regarding resilience, all networks are at a medium level. The technology network is the most resilient but was the most affected by COVID-19, while the economic network resisted and adapted to the shocks, gradually becoming more resilient. The population and information networks are the least resilient, with no significant improvement resulting from poor structural steepness, disassortativity, and agglomeration characteristics.

For the resilience of urban agglomerations with composite multi-networks, we propose a resilience improvement framework for smart city networks that synchronizes system optimization and node improvement. This framework provides a reference for intercity networks with similar characteristics in other smart regions, especially for the resilience construction of smart urban agglomerations in non-highly developed inland areas. For system optimization, efforts should be made to improve the ordering degree of subnetwork resilience and the synergy of their composite networks. Improvements targeting dominant and redundant nodes emphasize different aspects. Measures from the perspective of disaster prevention and mitigation should be taken to reduce the risk of failure of dominant cities, while strategies such as balancing resource allocation and strengthening node functions are applicable to redundant cities. Further, the framework emphasizes a bottom-up participatory approach to governance, which is essential to address the political and economic challenges of intercity collaboration and to ensure that intercity networks are aligned with residents' preferences [71].

With globalization and smartening, cities are becoming increasingly interconnected, which puts more pressure on co-construction and sharing in smart city networks [91]. Although the analytical network resilience approach and policy recommendations in this paper can provide valuable information for smart city network planning in other regions, our study had some limitations. Firstly, considering network data accessibility, availability, and continuity, we had to give up on expanding the dimensions to other more integrated, comprehensive, and scientific dimensions such as data, ecology, and governance. This limitation may have resulted in an incomplete representation of the factors influencing smart city network resilience, especially the absence of governance-related metrics that prevent a deeper exploration of institutional frameworks and their role in network cohesion and resilience. Future work will be devoted to building smart city networks in other dimensions, such as data flows, ecological indicators, and collaborative governance. Advanced technologies such as multi-modal data fusion and remote sensing may help to overcome challenges in data availability. Secondly, despite the fact that the research framework is generalizable and replicable, a single case study will inevitably limit the generalizability of the findings to a certain extent to other regions. Future research will conduct a comparative study of urban agglomerations with different socio-economic backgrounds and stages of smart city development, which will help refine the proposed framework and strategy. Thirdly, this study did not make any improvements in resilience measurement indicators, but the traditional topological indicators may limit the accuracy of resilience assessment of smart city networks. Future research will explore the integration of advanced indicators into our multidimensional network resilience research framework to further improve the accuracy and applicability, such as the connectivity measurement metrics proposed by Alenazi et al. based on graph theory algorithms, which were used to assess the resilience of smart city communication networks [92,93].

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Appendix A. Supplementary Information

Table A1. Data sources for the construction of the city networks.

Network	Data	Source	Description
Technology innovation network	Co-invention patent data in the digital industry	China National Intellectual Property Administration (CNIPA) (https://pss-system.cponline.cnipa.gov.cn/seniorSearch (accessed on 25 January 2024))	The screening of patent data related to the digital technology industry refers to the document published by CNIPA, *Table of Reference Relationships between the Core Industry Classification of the Digital Economy and the International Patent Classification (2023)*. We only collected patents submitted by companies, universities, and research organizations; that is, patents registered by individuals were excluded [61,94].

Table A1. *Cont.*

Network	Data	Source	Description
Population flow network	Population migration index	Autonavi Map (https://report.amap.com/migrate/page.do (accessed on 29 November 2023))	Autonavi Map records big data on daily population inflows and outflows between cities through location-based services and measures the actual population migration index, which covers all modes of transport [60,95]. As this dataset started in June 2018, we collected the daily average actual population migration index from June to December each year to control for the time variable.
Information flow network	Search frequency for city information	Baidu search index (https://index.baidu.com/v2/index.html#/ (accessed on 2 December 2023))	The Baidu search index identifies the search volume for specified keywords by Baidu users (China's largest search engine) in a specific region and is a representative data resource for measuring information flow [96]. We searched the Baidu Index website using city names as keywords and collected daily average data according to users in different cities.
Economic connection network	Night lights data; Urban resident population; Intercity geographic distance	Improved DMSP-OLS-like data (https://doi.org/10.7910/DVN/GIYGJU (accessed on 16 January 2025)); China City Statistical Yearbook; Autonavi Map	Compared with GDP, night light data has the advantages of being highly objective, time-stable, and comprehensive. Improved DMSP-OLS-like data have been shown to accurately describe the socio-economic level in China [97]. We characterize the level of economic development of a city by dividing the total value of the city's night lights by the corresponding city area to obtain the average night light value.

Table A2. Methods used to construct the networks.

Network	Construction Method	Calculation Method
Technology innovation network	Various organizations are agents of the network nodes, and the network edges represent the cooperation between intercity organizations.	Counting the number of patents co-invented by intercity organizations in each year from 2018 to 2022.
Population flow network	City populations are proxies for the city nodes, and their migration between any two cities represents the links.	Daily average of the sum of actual migration indices between two cities.
Information flow network	Internet users are viewed as agents whose behavior leads to the flow of information between cities. Whenever they search for another city, city links are generated.	Multiplication of average daily Baidu search index between two cities [5].
Economic connection network	Gravity modeling is used to establish links between city nodes, with the gravity degree index reflecting the strength of the links.	Equation (1)

Appendix B. Calculating the Synergistic Degree of Composite Systems

The theoretical core of synergetics is to analyze how orderly structures emerge spontaneously in time, space, and function through synergies. As a framework for studying the self-organization of complex systems, synergetics has been widely used to analyze common problems in interdisciplinary fields. Evaluations of the synergistic effects of a composite system help to reveal the system's evolutionary pattern and its sustainable development. In this paper, the smart city network is regarded as a composite system consisting of an interactive flow of elements: technology, economy, population, and information. Therefore, the composite system resilience is the result of competition and collaboration across the four network subsystems. A composite system synergy model was established to evaluate the synergistic smart city network resilience, which included an indicator ordering degree model, a subsystem ordering degree model, and a composite system synergistic degree model. The model design is described in the following.

First, the indicator ordering degree model is established. Define the composite system $S = (S_1, S_2, S_3, S_4)$, where S_1, S_2, S_3, S_4, respectively, represent the technology, population, information, and economic network subsystems. Based on synergy theory, the indicator that determines the system's evolution is the order parameter, the ordering degree of which determines the subsystem's operation ordering degree. In this paper, the subnetwork hierarchy, matching, agglomeration, transmissibility, and diversity are the order parameters, which are denoted $h_{ij} = (h_{i1}, h_{i2}, h_{i3}, h_{i4}, h_{i5}), (i = 1, 2, 3, 4)$. Usually, there are two different effects of order parameters on the system: the positive indicators are positively correlated with the system operation, and the negative indicators are negatively correlated with the system operation. Only matching is a negative indicator because all subnetworks are disassortative; that is, their indicator values are negatively correlated with network resilience. The formula for the indicator ordering degree is Equation (A1), through which we can determine the ordering degree for each indicator in each sub-system at different times.

$$\mu_i(h_{ij}) = \begin{cases} \frac{h_{ij}-\alpha_{ij}}{\beta_{ij}-\alpha_{ij}}, \ h_{ij} \text{ is a positive indicator} \\ \frac{\beta_{ij}-h_{ij}}{\beta_{ij}-\alpha_{ij}}, \ h_{ij} \text{ is a negative indicator} \end{cases} \tag{A1}$$

In Equation (A1), $\mu_i(h_{ij}) \in [0, 1]$ denotes the contribution of the order parameter to the subsystem ordering; the larger the value, the larger the contribution of h_{ij} to the ordering of subsystem S_i. α_{ij} and β_{ij} are the minimum and maximum values of h_{ij} in the study period.

Second, establish the subsystem ordering degree model. The subsystem resilience ordering degree at different periods is the integration of the ordering degree values of the five indicators at each time. We used a linear average weighting method to calculate each sub-system's ordering degree. Let $\mu_i(h_i)$ be the ordering degree of each subsystem, which is measured using Equation (A2).

$$\mu_i(h_i) = \sum_{j=1}^{5} \omega_j \mu_i(h_{ij}), \omega_j \geq 0, \sum_{j=1}^{5} \omega_j = 1 \tag{A2}$$

Finally, establish the composite system synergistic degree model. The composite system synergy determination process is a dynamic analysis process based on time series. Let the composite system synergy CS be from moment t_0 to t_1, and the ordering degree of each subsystem be $\mu_i^0(h_i)$ and $\mu_i^1(h_i)$. CS for the interval t_0 to t_1 can be obtained using geometric averaging, where the coefficients ϖ are used to reflect the direction of the subsystems' effect on the composite system synergy, as shown in Equation (A3).

$$\begin{cases} CS = \varpi \sqrt[n]{\left| \prod_{i=1}^{n} \left[\mu_i^1(h_i) - \mu_i^0(h_i) \right] \right|} \\ \varpi = \frac{\min\left[\mu_i^1(h_i) - \mu_i^0(h_i) \right]}{\left| \min\left[\mu_i^1(h_i) - \mu_i^0(h_i) \right] \right|} \end{cases} \tag{A3}$$

In Equation (A3), when n is 2 or 5, the synergy of the two–two sub-networks and the overall composite network can be respectively calculated. The CS value is in the range $[-1, 1]$; the larger the value, the higher the system synergy, and vice versa.

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