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Decision-Making Based on Network Analyses of New Infrastructure Layouts

Shan Luo [1], Tao Wang [1,*], Limao Zhang [2] and Bingsheng Liu [1]

[1] School of Public Policy and Administration, Chongqing University, Chongqing 400044, China; luoshan556@163.com (S.L.); bluesea_boy_1979@163.com (B.L.)
[2] School of Civil and Hydraulic Engineering, Huazhong University of Science and Technology, 1037 Luoyu Road, Hongshan District, Wuhan 430074, China; zlm@hust.edu.cn
* Correspondence: wangtaothu@163.com

Abstract: New Infrastructure (NI) has gradually become a new driving force for regional economic growth and an important part of the construction of new urban infrastructure in many countries, including China. Compared with traditional infrastructures, these NIs have mutually supportive functions and complex interrelationships that create interconnected networks of resources, information, and other interactions during the construction of the NIs. Therefore, it is important to analyze such correlation networks and explore their formation mechanisms in order to develop more scientific and reasonable strategies for NI investment and construction. In this study, the interdependence between NIs in Chongqing was analyzed as an example. Social network analysis (SNA) was used for the overall characteristics of the interdependency network of the NIs and an exponential random graph model (ERGM) was used to reveal the formation mechanism of this network. The results showed that information infrastructure is the key node for enhancing the effectiveness of Chongqing's NI needs and its government should play a coordinating role. The network of related relationships is characterized by "reciprocity" and "small group". The aggregation of NIs with such characteristics can produce an agglomeration effect. So, in the planning of NIs, the coordination among management departments should be strengthened and project locations should be reasonably arranged according to the functional interactive characteristics of the projects.

Keywords: new infrastructure; network analysis; decision-making; exponential random graph model

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1. Introduction

Against the backdrop of the obvious downward trend of the world economy and the emergence of new breakthroughs in technology development, new infrastructures based on 5G, the Internet of Things, big data, artificial intelligence, and cloud computing have gradually become the new driving forces of regional economic growth. The notion of new infrastructure construction was initially proposed in December 2018 by China's Central Economic Work Conference [1], which defined 5G, artificial intelligence, the industrial Internet, and the Internet of Things as New Infrastructure (NI). In April 2020, China's National Development and Reform Commission (NDRC) clarified for the first time that NI includes three aspects: information, integration, and innovation infrastructures. Information infrastructures include communication network infrastructures, technology infrastructures, and arithmetic infrastructures. These include, for example, 5G, the Internet of Things, Industrial Internet, satellite Internet, artificial intelligence, cloud computing, blockchains, data centers, and intelligent computing centers. Integration infrastructures include intelligent transportation infrastructures, intelligent energy infrastructures, etc. Innovation infrastructure include major science and technology infrastructures, science and education infrastructures, industrial technology innovation infrastructures, and other content. Internationally, the concept of NI has not been commonly proposed, but some scholars have proposed that smart cities include smart infrastructures, smart buildings, smart transportation, and smart governance [2]. In 2018, the government of the United States proposed a trillion-dollar infrastructure reconstruction plan, with over $900 billion allocated to next-generation information and energy infrastructures, as well as the intelligent, digital transformation of traditional infrastructures. The European Commission also launched the "New Industrial Strategy for Europe" in March 2020, advocating a digital future for Europe while increasing research and funding for artificial intelligence, 5G, and data and metadata analyses. Since the outbreak of COVID-19 pandemic, China has evolved the NI plan into a national strategy. According to the data from CITIC Foundation for Reform and Development Studies, the Chinese government has invested $154–$279 billion in new infrastructure in 2021. Xi Jinping has underscored the need to "expedite the construction of NI projects such as 5G networks and data centers", which is beneficial to "foster new economic growth points and form new driving forces for development" [3]. Compared with traditional infrastructures, smart infrastructures are safer, more efficient, and more reliable. According to some experts, investment in NI construction will continue to rise in the future in order to promote improved infrastructure integration and smart cities [4]. To reduce the epidemic negative impact of the epidemic as soon as possible and promote the economy return to the normalcy, it is necessary to drive the economy by focusing on the NI [5].

Traditional infrastructures in urban development are linked primarily through functional or geographic interactions. Disruptions of critical infrastructure networks (e.g., water, communications, power, and transportation) by urban flooding would result in disruptions of health care facility operations [6]. In 2003, a power outage in the northeastern United States caused water contamination, transportation gridlock, and skyrocketing fuel prices in adjacent areas [7]. However, NIs rely more on interactions among data, information, and knowledge to generate interdependency. Therefore, the relationships among them are frequently more complicated and interchangeable [8]. In different application scenarios, NIs would generate distinct interactions based on their own characteristics and create new combinations. For example, when 5G technology and UHV power grids are employed as separate NI projects, they play roles in the communication and power infrastructures, respectively, but when the NIs are combined, cross-domain applications such as smart grid and robot inspection emerge [9]. Therefore, identifying the relationship between NIs and construction decision-making is of great significance to the effective allocation of investment in local infrastructure projects, increasing the utilization rates of NI projects, and improving urban infrastructure construction. Current large-scale infrastructure projects are experiencing major delays, cost overruns, and inefficiency [10]. Zuluaga pointed out that flexibility in decision-making was important in infrastructure development [11]. Therefore, there is an urgent need to find an effective method to guide the development of NIs.

A large number of studies have used simulation models, social network analysis (SNA), and regression models to analyze infrastructure networks. These methods have certain drawbacks. For example, SNA only focuses on the associations between actors but tends to ignore the relationships between other parties [12]. Regression models assume independence between variables while ignoring the interactions and dependencies [13]. These classic methodologies are unable to account for the influence of the endogenous structure formed by two actors in a network on a third party [14]. Unlike those studies that have focused on the associations between established infrastructures, our study examined the interactions among NIs and used SNA to construct networks of association relationships. In addition to the interaction between NIs, the impact of other factors on the network must be considered, and we also considered the interdependency between NIs. As a result, this study combined the SNA and the exponential random graph model (ERGM), which not only analyzed the connections of other factors other than the NI, but also took the interdependence of virous variables (e.g., node attribute, homophily, and network structure) as a premise, compensating for the limitations of the SNA and regression model methods' single-use. We identified the main factors influencing the NIs at the overall level, and explored the interactions among the node attribute variables, homophily variables, and network structure variables, as well as the influences of these interactions on the formation of the networks at the micro-level. An analysis of the formation mechanism of an NI association network can provide suggestions for the rational planning of NI layouts, as well as provide theoretical and decision-making bases for governments to reduce risks and improve the efficiency of capital allocation.

2. Literature Review

2.1. Concepts and Research Statuses of Traditional and New Infrastructures (NIs)

Critical infrastructure networks in cities are the building blocks and arteries for the proper functioning of cities [15]. National security, economic prosperity, and social stability cannot be achieved without a stable, reliable, and continuously operating critical infrastructure. The U.S. Critical Infrastructure Protection Board identifies critical infrastructure in cities as telecommunications, electric systems, gas and oil systems, banking and finance, transportation, water systems, government services, and emergency services. Together, these critical infrastructures form urban lifeline systems that play an essential role in improving the quality of urban services and the standard of living of urban residents [16]. The combination of digital technology and physical urban infrastructure has given rise to the concept of smart infrastructure [17]. Generally speaking, there is no consensus on the concept of NI, but its scope, which includes 5G networks, artificial intelligence, the industrial Internet, the Internet of Things, data centers, and charging piles, is recognized by most scholars, so we can define these areas as NI in a narrow sense [18]. A more official and authoritative definition proposed by NDRC includes information, convergence, and innovation infrastructures [1]. There are five features to the NI: its core is digital technology, its body is new fields, its driving force is technological innovation, its primary form is virtual products, and its primary carrier is the platform [19]. Smart infrastructures, according to the Cambridge Center for Smart Infrastructure and Construction, are "the result of combining physical and digital infrastructures to provide better information for better, faster and less costly decisions". They are the closest to the concept of the NDRC, but the connotations of NI are much broader. Current research on NIs has focused on conceptual interpretations, related applications, current development statuses, and effects on urban development [20–23]. As an emerging hotspot in the field of infrastructure, the research is still generalized at the macro-level. However, this study went beyond superficial overall analyses of current infrastructure networks to an examination of the micro-relationships between the NIs and the formulation of recommendations for the construction of urban NIs.

2.2. Study of Interactions between Infrastructures

To maintain their functions, various types of urban infrastructures create a variety of relationships during their operations and form a "network of networks", which Rinaldi classified as physical, cyber, geographical, and logical [24]. Following Rinaldi, Dudenhoeffer considered the policy and social linkages between infrastructures [25]. Wallace classified the relationships between infrastructures as input, mutual, shared, exclusive, and collocated from the perspective of resource and information interaction [26]. Zhang suggested four categories of linkages between infrastructure: functional, physical, budgetary, and market [27]. Other scholars have studied the relationships between critical infrastructures from the perspective of network vulnerability. For example, Blokus claimed that the failure of one critical infrastructure would reduce the security of other infrastructures [28]. Zorn studied the extent and frequency of damage, as well as the extent of the failures of infrastructures in New Zealand with various linkage strengths during disasters and discovered that the strengths of the linkages between the infrastructures had significant effects on how well the infrastructures functioned [29]. Previous studies on interactions between infrastructures generally started from dependencies and ended with the effects on the vulnerabilities of infrastructure network [30,31]. However, these studies were more focused on ex-post reaction strategies after the cascade vulnerability developed, rather than a deeper analysis of the reasons for the formation of these interactions. This study further explored the interactions of infrastructure network nodes and network formation mechanisms to provide an in-depth and extended investigation of the linkages between NIs. We aimed to provide guidance on decision-making prior to the construction of NI.

2.3. Methods Used to Study Infrastructure Interdependency

Much of the research on the relationships between critical infrastructures has been conducted by simulation models, which have mainly included the following types. First, agent-based models, such as that of Thompson, propose an agent-based critical infrastructure model (ICIM) to identify potential weaknesses and points of failure in the interdependence between electricity and water networks [32]. Bucovetchi et al. also used an agent-based model to verify that critical air transportation infrastructure depended on space systems [33]. The second type is economics-based input–output models, whose main assumptions state that infrastructures with significant numbers of physical connections have similar degrees of economic interactions, i.e., the relationships between infrastructures can be described by economic quantities [34]. The third type is system dynamics-based models, which represent the correlations between infrastructures through causal loops and flow diagrams. They are mainly applied to macroscopic modeling of the infrastructure dynamics of countries or large cities [35,36]. The fourth type uses graph theory and network theory to evaluate the relationships between infrastructures. The nodes in their network diagrams are used to represent the infrastructures and the connected edges between the nodes are used to describe their associations [37,38]. These approaches are built on existing networks and are centered on the correlations of infrastructures, as well as the construction of analytical frameworks [39,40], infrastructure cascade failures, and vulnerabilities [41,42]. However, the deeper motives of network formation have not been directly observed while analyses of the network formation mechanisms and node interaction processes have been lacking [43]. All three approaches, agent-based models, system dynamics-based models, and input–output models, are inevitably subjective in describing interdependency and influencing research findings [44–46]. Regression models have been used in earlier studies to analyze the interactions between infrastructures [47,48], however, regression models are based on the assumption of actors' interdependency, and infrastructures are typically related rather than independent of one another. Therefore, this study used an ERGM as an analytical tool. This type of model is based on the interdependence of variables, focuses on the features of network nodes and the network formation mechanism, and explores whether specific substructures in the network affect its development. The model is based on social network theory, which states that the formation of a network is closely related to the network's structure, node attributes, and internodal relationships [49]. Traditional quantitative research relies on the independence of the observed object, but the advantage of this model is its ability to test whether the pooling of local nodes could generate global network characteristics and properties [50]. Jang et al. used an ERGM social selection model to analyze the formation mechanism of European nuclear trade networks and proposed the applicability of the model to the study of international relations [13]. Belkhiria employed the ERGM model to analyze a movement network of nomadic herds, then explained and predicted the formation mechanism of this network in terms of environmental, economic, and sociocultural factors [51]. Li investigated the homophily effects of actor collaboration networks in the resilient planning and management of infrastructure systems [52]. With the help of an ERGM model, our study analyzed the interactions of node attribute variables, homophily variables, and network structure variables in the NI interdependency network of the city of Chongqing, as well as examined how these interactions affected the formation of the network and what the causes of these results were.

3. Methodology

3.1. Data sources and Data Processing

The data were sourced between 21 June 2020, and 27 December 2021 from a variety of sources, such as government documents, news reports, and situational reports, as well as publicly available textual materials, such as reports from authoritative news portals, local newspapers, and social media. The data were organized to obtain structured data on NI projects in Chongqing and their associated relationships.

For data processing, we first determined the main body of NIs from a list of major municipal construction projects published on the website of the Chongqing Municipal People's Government and finally obtained 27 NI project nodes, which were coded and categorized according to their respective attributes. Information infrastructures were coded as A1–A7, convergence infrastructures were coded as B8–B20, and innovation infrastructures were coded as C21–C27. The Supplementary Materials lists the project names and the management departments to which they belong. In determining the interdependency between NI projects, keyword information was first extracted by manually mining related materials [53]. If the implementation of an NI function required the participation of another NI or an NI could provide support to another NI to realize the function, then an interaction relationship was considered to exist between the two NIs [54]. In this case, the relationship was regarded as a two-way connection, whereas other relationships were regarded as one-way connections. For example, as in the article, "Analysis of the Application of Cloud Computing in Radio and Television Networks", keywords such as "Tencent Cloud exports technology to help Chongqing Cable further transform and upgrade to multimedia information services" appeared [55], and we determined that B8 was supported by A3 in implementing multimedia information service functions. This support was labeled as a one-way association between the two nodes. Finally, we obtained a total of 199 connections and converted the obtained text data into a 0–1 matrix, where "1" indicated a correlation between the NI projects and "0" indicated no correlation. Then, we constructed a structured data adjacency matrix and entered it into the social network analytical software, UCINET, to derive the interdependency network among the NI projects in Chongqing.

3.2. Overall Interdependency Network and Exponential Random Graph Model (ERGM)

We used UCINET to construct the interdependency network, then calculated the overall interdependency network-related indicators and derived the descriptive statistics. Next, we formulated an ERGM to analyze the effects of the NI projects' interdependency network structure and node attribute variables on the overall interdependency network. ERGM is a tie-based model that infers the processes and drivers that lead to the establishment and maintenance of network ties to account for their presence (or absence). [56]. ERGM uses a logistic regression-like statistical form, so the interpretation of the coefficients is similar to that in a logit model [57]. The main advantage of ERGM is that it simulates the dependencies between nodes in a network formation and hence provides a better fit. [58]. The traditional assumption that quantitative research relies on the interdependence of the observed object is disproved. Node attribute factors and network structure are incorporated into the same research framework, and the contribution of multiple factors acting together to form the network is analyzed. The ERGM model takes the following general form:

$$P(Y|y) = \frac{\exp\{\theta_t g(y, X)\}}{k} \tag{1}$$

where Y denotes the random network set of the NI interdependency network. Y = 1 when there is a connection between any two points i and j, otherwise Y = 0. y represents the observed real network structure; X denotes the attribute variables of each node in the NI interdependency network; $g(y, X)$ represents the set of each statistic, including the network structure variables, node attribute variables, and homophily variables; the constant k ensures that the probability of the emerging NI interdependency network structure is between 0 and 1; θ_t denotes the parameter to be estimated; t denotes the first few parameters to be estimated, i.e., the parameter corresponding to the network structure statistic. The significance of θ_t and the magnitude of its value were used to determine the degrees of the influences of different factors on the formation of the NI interdependency network. The model was validated by the Statnet package in R language using Markov chain Monte Carlo maximum likelihood estimations. The degree of the fit of the ERGM model was determined with the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). Smaller values of these two metrics indicated a better fit.

3.3. Variable Selection

3.3.1. Node Attribute Variables

Centrality is the degree of power and central position of actors in social network, which includes degree centrality, betweenness centrality, and closeness centrality. Degree centrality measures the centrality of nodes in the network, reflecting the difference in the location or advantage of nodes [59]. The higher degree centrality of the NI, the greater position advantage of the NI in network. Betweenness centrality is a measurement of the extent to which an actor has control over information flowing between others [60]. A point with high betweenness centrality can play a crucial role as an intermediary and bridge. If this point is lost, then related nodes may lose their connections. Therefore, we considered betweeness centrality was the position that an NI occupied between two or more NIs in the network. Freeman pointed out that if the focus was on interaction activity, the degree centrality could be employed; if the control of interaction was studied, the betweenness centrality could be used [59]. Both of them were the main concerns of our study. Hu discovered the most important nodes that must be taken into account while designing urban disaster prevention through the examination of degree centrality. Additionally, they investigated the nodes occupying the critical paths in the network of typhoon cascading effects using betweenness centrality [61]. At the same time, the results of the closeness centrality are not as precise as the betweenness centrality [59]. We concentrated on the differences in node location dominance as well as nodes' interactions. Therefore, degree centrality and betweenness centrality were selected and measured by UCINET.

3.3.2. Homophily Variables

Homophily variables were selected to measure the model's organizational homophily and geographic homophily. Organizational homophily existed when the subjects of a certain number of NI projects were under the administration of the same governmental body. During data processing, such subjects were uniformly labeled as "1" if under the same municipal department but "2" if belonging to the same agencies directly under a city's government. Geographic homophily referred to the distribution of the subjects in adjacent regions. Subjects located in the same central urban area were labeled as "1", whereas those located in districts and counties were labeled as "2".

3.3.3. Network Structure Variables

The network structure variables should be selected to avoid the risk of model degradation, so the number of edges (E_D), reciprocity (M_U), two-path (T_W), and geometrically weighted edge-wise shared partners (G_E) were selected as indicators to examine the network structure. The number of edges plays a reference role in each model as a control variable. Reciprocity is used to measure the convergence of reciprocity between nodes. Two-path measures "transitivity" in a directed network and refers to the number of structures in which an NI project node acts as a "bridge" to two other nodes. Geometrically weighted edge-wise shared partners measures the number of nodes with shared partnerships and refers to the tendency of the paths of the interactions between different NI projects to form a closed triangular structure, i.e., the number of structures in which two NI projects have a joint partner.

4. Empirical Analysis

4.1. Analysis of the Overall Network Characterization of NI Projects in Chongqing

UCINET was used to construct the overall network diagram (Figure 1), in which the nodes represent the NI projects in Chongqing, the connecting lines between the nodes indicate the interactions between the NI projects, and the arrows point to the causality of the interaction relationships. A total of 199 links were eventually obtained. This support was labeled as a one-way association between the two nodes. As shown in Table 1, transforming the obtained text data into a 0–1 matrix and entering them into UCINET calculated the number of nodes to be 27, the number of network edges to be 199, and the density to be 0.274, indicating that the overall network is relatively loose and the overall interdependency between the NI subjects is low. We built a directed network and the measurements showed that the average path length of the network was calculated to be 2.052. It meant any two NI must pass through at least three project nodes to achieve connectivity, indicating that there are certain barriers and limitations to resource transfer and information exchange between NI projects. The average clustering coefficient of the network is 0.436, which means that the network's connectivity is not high and the synergistic connections between neighboring nodes are relatively poor. Reciprocity analyzes the mutually beneficial relationship between two actors in network, and transitivity refers to the transfer of the relationship between three actors [62]. The network exhibited some reciprocities and transitivities, with values of 0.5000 and 0.576, respectively. It implied that NIs were interconnected, but the information was not flowing efficiently, which made it challenging for NIs to exchange opportunities and transfer resources.

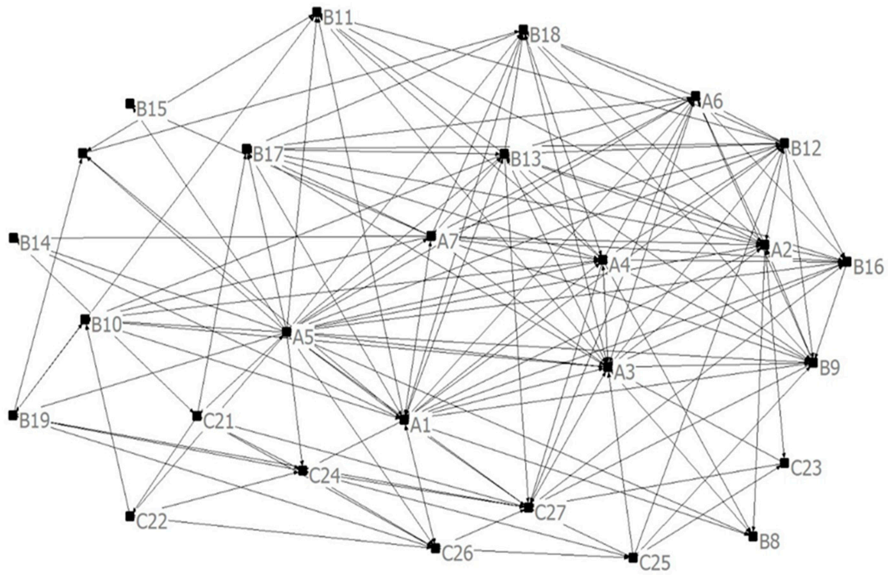

Figure 1. Overall interdependency network of NI in Chongqing.

Table 1. Results of social network analysis.

Statistical Indicator	Numerical Values
Nodes	27
Edges	199
Density	0.274
Average path length	2.052
Average clustering coefficients	0.436
Arc-Based Reciprocity	0.5000
Transitivity	0.5764

Centrality, cohesive subgroup analysis, structural holes, and peripheral analysis were also selected to measure the overall structure of the network.

We need to obtain a sense of the location of each node of the NI network and the distribution of rights. The centrality can serve this purpose. The centrality refers to the number of shortest paths through a node and measures the node's role in the whole network. A node with a higher centrality is comparatively easier to become the critical node of the network. The centrality includes degree centrality, betweenness centrality, and closeness centrality. In a directed network, degree centrality is divided into out-degree centrality and in-degree centrality, which reflect the ability to issue or receive other nodes, respectively. Betweenness centrality means that a node is on the path of all nodes in the network, reflecting the node's ability to control resources [59]. Closeness centrality is divided into in-closeness centrality and out-closeness centrality in a directed network, which reflects the shortest distance between nodes. Closeness centrality measures one node to the others nodes' sum distances. If the length of node's shortest paths to other nodes in the network is small, then the node has a high closeness centrality, and can obtain resources and information efficiently [63].

According to Table 2, the high in-degree of A3 and A1 indicates that many nodes are receiving information from them, and they are active members of the network since they can actively establish connections with others. The top five rankings of out-degree centrality were A5, A1, A3, A4, and B13, respectively. It shows that there are more messages sent to these NIs in the network, they receive more attention and are the "stars" of the network. Meanwhile, A1 and A3 obtain a higher betweenness centrality, indicating that they hold more power in the development and utilization of resources in the network. The in-closeness centrality and out out-closeness centrality of A1 were both in a high position, showing that it has the shortest distance and highest efficiency in acquiring and transmitting external resources and information.

Table 2. Results of centrality.

In-Degree		Out-Degree		Betweenness		In-Closeness		Out-Closeness	
A3	16.000	A5	24.000	A1	22.385	A1	40.625	A5	92.857
A1	14.000	A1	17.000	A3	14.571	A3	40.625	A1	70.27
C27	12.000	A3	15.000	A4	9.032	C27	38.806	A4	66.667
B17	11.000	A4	15.000	A5	8.852	B11	37.681	A3	65.000
B18	10.000	B13	13.000	A2	8.089	B10	37.681	A2	63.415

Cohesive subgroup analysis focuses on the internal structure of the overall network, which is a manifestation of affinity [64]. It helps to understand the role of NIs in the network, and can show the structural relationship and affinity between NIs. The results of the cohesive subgroup analysis showed that the interdependency network of NI projects in Chongqing contains three cohesive subgroups, of which each showed a weak linkage relationship. A1, A5, B8, A3, and A6 repeated in these three cohesive subgroups. These NI projects are involved in various relationship chains of the integral network, the flow and diffusion of information and resources among them are faster, with relatively more minor contradictions and conflicts, and there are strong interactions with other NI projects in the subgroup, as shown in Table 3.

Table 3. Results of cohesive subgroups.

No.	Projects
1	A1,A5,B8,A3,A6,C21,B10,B11,B12,C22,C24,C26,A4,A2,B13,B9,A7,B14,B15,B16,B17,B18,C27,B19,B20
2	A1,A5,B8,A3,A6,C21,B10,B11,B12,C22,C24,C25,C26,A4,A2,B13,B9,A7,B16,B17,B18,C27,B19
3	A1,A5,B8,A3,A6,C21,B10,B11,B12,C23,C24,C25,C26,A4,A2,B13,B9,A7,B16,B17,B18,C27,B19

A structural hole refers to the lack of direct connections or intermittent relationships between some nodes [64], which would be in a strategic position of multi-group information gathering, thus becoming a crucial path of information flow in the NI network, as well as having information and control advantages. The results of the structural hole measurements are shown in Table 4. The smaller limit systems of A5, A1, and A3 indicated that they occupy more structural holes in the NI interdependency network in Chongqing while being intermediaries connecting the nodes in the overall network, as well as acting as bridges for the resource flows and information exchanges among numerous NI projects.

Table 4. Results of structural hole analysis (top five).

No.	Effsize	Efficie	Constra	Hierarc
A5	17.296	0.721	0.162	0.058
A1	13.581	0.679	0.19	0.076
A3	10.903	0.606	0.214	0.064
A4	8.146	0.543	0.263	0.082
A7	7.714	0.514	0.266	0.083

In peripheral analysis, there are two types of actors, which are cores and edges. The former would have tighter ties among NIs, whereas the latter would have looser ties. As shown in Table 5, the core layer of the NI interdependency network in Chongqing has 11 nodes, including B8, A1, A2, and B9, while the edge layer contains 16 nodes, including B20, B10, and B11, respectively. NI projects at the core have an absolute advantage in the overall network of associations and are in a privileged position in terms of capital investment and acquisition of information.

Table 5. Results of peripheral analysis.

Core Layer	B8,A1,A2,B9,B8,B12,A4,A5,B13,A6,A7
Peripheral layer	C21,B10,B11,C22,C23,C24,C25,C26,B14,B15,B16,B17,B18,C27,B19,B20

4.2. Construction of ERGM Model of NI Network

Following the integral descriptive statistical analysis of the NI interdependency network in Chongqing, it was essential to explore further how the nodes in the network interacted with each other and the formation mechanism of this network in order to provide theoretical support for further rational planning of new urban infrastructure construction. Therefore, the following models were constructed for empirical analysis in this study. The specific processes for their construction are detailed in the Supplementary Materials.

$$P(Y = y|X) = \frac{\exp(\theta_1 E_D)}{k} \tag{2}$$

$$P(Y = y|X) = \frac{\exp(\theta_1 E_D + \theta_2 N_B + \theta_3 N_D + \theta_4 N_O + \theta_5 N_L)}{k} \tag{3}$$

$$P(Y = y|X) = \frac{\exp(\theta_1 E_D + \theta_6 M_U + \theta_7 T_W + \theta_8 G_E)}{k} \tag{4}$$

$$P(Y = y|X) = \frac{\exp(\theta_1 E_D + \theta_2 N_B + \theta_3 N_D + \theta_4 N_O + \theta_5 N_L + +\theta_6 M_U + \theta_7 T_W + \theta_8 G_E)}{k} \tag{5}$$

4.3. Analysis of Results

Parameter estimation was performed for the four models by running the Statnet data package in R. Model 1 was used as the reference model to which different statistical variables from the other three models were added for simulation. The results of the ERGM parameter estimation are shown in Table 6.

Table 6. ERGM estimation results.

Statistical Items	Model 1	Model 2	Model 3	Model 4
E_D	−1.38 [c]	−2.93 [c]	−3.62 [c]	−3.92 [c]
	(0.08)	(0.34)	(0.26)	(0.32)
N_B		0.001		0.00
		(0.00)		(0.00)
N_D		0.06 [c]		0.02 [a]
		(0.02)		(0.01)
N_O		0.08		0.06
		(0.17)		(0.16)
N_L		0.04		0.02
		(0.21)		(0.15)
M_U			0.72 [b]	0.67 [a]
			(0.27)	(0.27)
T_W			0.02	−0.01
			(0.02)	(0.03)
G_E			1.18 [c]	1.16 [c]
			(0.22)	(0.23)
AIC	996.46	967.67	924.39	919.41
BIC	1001.36	992.17	943.99	958.61
Log Likelihood	−497.23	−478.84	−458.19	−451.71

[a] Significant at alpha level of 0.05. [b] Significant at alpha level of 0.01. [c] Significant at alpha level of 0.001.

The model passed the significance test in general while the values of the goodness-of-fit (GoF) indicators, which are AIC and BIC of model 2, 3, and 4 all decreased significantly, with model 3 dropping more than model 2, indicating that the characteristics of the network structure variables played critical roles in the formation of the network of NI linkages in Chongqing. Model 4 provided the highest GoF and indicated that the model containing both node attribute variables, homophily variables, and network structure variables reflected the NI interdependency network more realistically and was proven to be robust.

The specific analysis is as follows:

(1) The edge coefficient was −3.92 ($p < 0.001$), which indicates that a random process does not generate the establishment of the NI interdependency network in Chongqing and that the actual NI interdependency network exhibits sparse network characteristics, which are consistent with the results of the UCINET analysis, in which each additional association interaction between NI subjects in the network, on the contrary, decreases the probability of new edge formation in the overall network.

(2) The coefficient of node centrality was 0.02 ($p < 0.05$) and the result is significant, indicating that NI projects with a strong degree centrality share more interactions with other NIs, i.e., nodes in the central position can exert more crucial roles, such as resource control and information exchange, in the interaction links between NI subjects. The betweenness centrality in the node attribute variables was not significant, indicating the absence of NI projects that could effectively play the role of intermediary bridges in the NI interdependency network in Chongqing. The reason for this may be Chongqing's late implementation of NI policies and many NIs still under construction, thus resulting in a lack of deep cooperation and interaction between projects and the intermediary bridge function played by key NI projects not being significant.

(3) The results of the empirical examination of both organizational and geographic homophily were not significant, suggesting that being under the administration of the same governmental body does not lead to enhanced linkages between NI projects, i.e., resource mobilization and information exchanges between NI projects under the jurisdiction of the same government department are not smooth and there may be blocked links. Furthermore, geographical adjacency does not strengthen the interactions between NI projects in Chongqing. Even if the projects are in the same area, there are minimal interactions in terms of resource mobilization, information exchange, and synergy and cooperation.

(4) The results of the empirical analysis of the network structure variables showed a positive significant coefficient of 0.67 ($p < 0.05$) for the reciprocity variable, indicating that the reciprocity between NI projects in Chongqing is high and there is a strong link between two related NI projects. They have no apparent hierarchical relationship in resource mobilization and information exchange but tend to have two-way cooperation and synergy. The coefficient of geometrically weighted edge-wise shared partners was 1.16 ($p < 0.001$), which is significantly positive. This result indicates that the closure mechanism has a significant effect on the formation of NI interdependency networks in Chongqing and the nodes tend to form a closed triangular structure between them, with significant transmission effects in the network.

The GoF was employed to measure the model's fitting degree and the index of model statistics was chosen to validate and compare the fitness of the simulated network to the real network, as shown in Figure 2. In Figure 2, the box plot represented the statistical outcomes of the simulated network, and the solid line displayed the statistical outcomes of the real network. The figure shows that the model fits well and that the real network and simulated network data mostly match, proving that the estimation results of ERGM are robust.

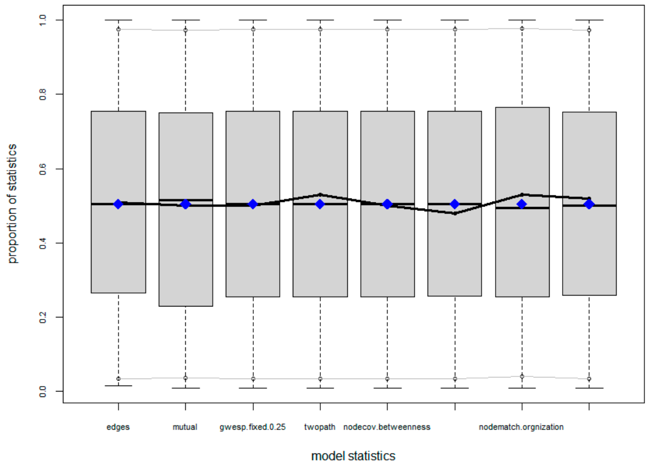

Figure 2. Robustness test results.

5. Discussion

(1) Among the NI projects in Chongqing, information infrastructure is a critical node in the network of associated relationships. Such NIs occupy beneficial positions and exert greater influence on resource mobilization and information exchange. According to the results of the aforementioned analysis, the centralities of projects such as 5G construction (A5), China Mobile Edge Computing Platform (A1), and Tencent Cloud Computing Data Center Phase II in Chongqing (A3) are the highest. However, the results of the structural hole measurement showed that these types of projects have smaller limit systems, and they are in strategic positions of multi-group information convergence, have information advantages and control advantages, and are the key to information and resource flows in the network. The results of the peripheral analysis measurement also showed that the above-mentioned NIs are in the core layer of the NI interdependency network in Chongqing. According to the ERGM analysis, the NIs with high degree centralities have significant effects on the overall network formation. They are in critical positions in the network, have robust connectivity with other projects, and play more vital roles such as resource control and information exchange in new infrastructural connections. Vulnerabilities in the city's metro transit network increase significantly when simulating attacks on infrastructure in critical locations and resulting in degraded performance. The information infrastructure around 5G, big data, cloud computing, and other technologies are key nodes in

the network associated with NIs that hold absolute advantages, as well as greater influence in terms of resource mobilization and information sharing. Therefore, when implementing NI projects in Chongqing, information infrastructure should receive more government support and resources while the investment scales and construction orders of NI projects should be reasonably arranged to prevent the disconnection of subsequent supporting facilities and ineffective investment due to blind construction. The development of information infrastructure has been shown to boost economic growth [65]. Therefore, the main direction for the future construction of NIs in Chongqing should be to increase the capital investment in information infrastructure and prioritize its construction order, make information infrastructure the navigator of NI development, and improve the overall construction levels of NIs in Chongqing.

(2) Governmental bodies should effectively coordinate information and resources to foster the construction of NI in Chongqing. The cohesive subgroup analysis revealed that NI projects such as China Mobile Edge Computing Platform (A1), Chongqing Tencent Cloud Computing Data Center Phase II (A3), 5G construction (A5), Chongqing Cable Smart Broadcast Data Center Phase I (B8), and Wanguo Data Chongqing Data Center (A6) repeated in each cohesive subgroup. They share information and resources while having higher group cohesion with more direct and frequent contact with each other. If these recurring nodes are removed from the subgroup, it would be challenging for the remaining nodes to form a network [66]. These NI projects are affiliated with different management departments (see the Supplementary Materials) and their jurisdictions are geographically dispersed. Such a situation may prove to be an obstacle to coordinating and linking cross-departmental information and resources, thus making synergy difficult among the NI projects. Collaboration among diverse actors is critical for effective resilience planning and management of interdependent infrastructure systems [67,68]. Therefore, synergy and cooperation between these departments should be strengthened during the construction and operation of NI projects in Chongqing, as shown in Figure 3. Strategic cooperation among Chongqing Cable Smart Radio and Tencent Cloud, Chongqing Municipal Commission of Culture and Tourism (M6), and Liangjiang New Area Management Committee (M3) can provide a good platform for information exchange and resource sharing through cross-sectoral linkages between the NIs. There are superior advantages in resource mobilization and information sharing for NIs within the same management department. For example, Chongqing Tencent Cloud Computing Data Center Phase II (A3) and Vanguard Data Chongqing Data Center (A6) are administered by the same Liangjiang New Area Management Committee (M3), whose guidance and coordination help them better perform their respective functions.

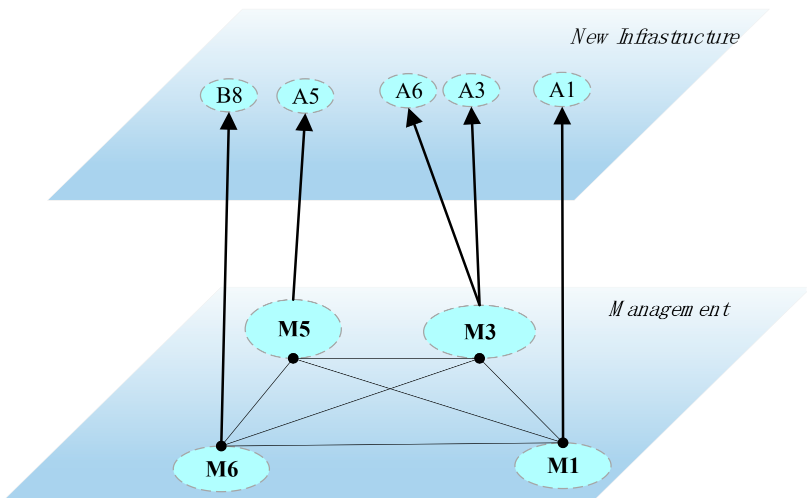

Figure 3. Collaboration between management departments.

(3) The NI interdependency network in Chongqing forms a phenomenon of small group aggregation while the NI projects tend to form reciprocal and closed triangle interactions with each other. This result is in accordance with Maghssudipour's findings [69]. There is a two-way connection between two NI projects with reciprocal structures, which tend to cooperate directly or indirectly, thus creating stronger interactions [70,71]. Network structure and node attributes are important factors that influence the formation of cross-sector collaborative networks. Providing specialized nodes for information and resource transfer can improve departmental communications, increase collaboration efficiency, and minimize the time it takes to respond to urban disasters [61]. Therefore, in the planning of NI construction in Chongqing, the collaboration between two projects with reciprocity can be further strengthened by increasing their management coordination and constructing the two projects in neighboring areas, thus better utilizing the effectiveness of the NI projects. Figure 4 shows the NI projects in Chongqing with reciprocal relationships. In addition, there are many closed triangular structures within the NI network in Chongqing that show prominent "small group" characteristics. These small NI clusters exert aggregation effects and tend to form synergy in terms of resource gathering and information interaction. Therefore, when designing new urban infrastructure, incorporating NIs with positive agglomerating effects into a functional cluster area would better utilize their respective functions.

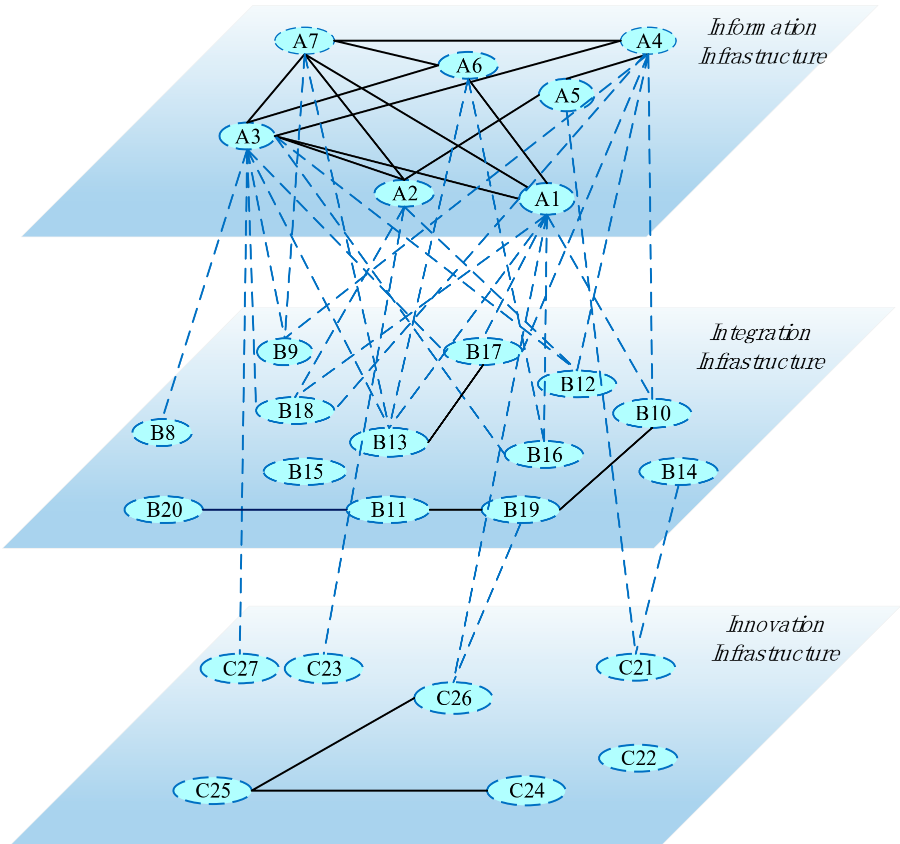

Figure 4. Reciprocal NI Projects.

(4) In the planning of NIs, their effectiveness can be better achieved only by strengthening the coordination of their subordinate management and the rational arrangement of project locations according to the inherent interactions between two NIs in terms of resources and information. According to the results of the ERGM analysis, organizational homophily and geographic homophily do not significantly affect the formation of the NI affiliation network in Chongqing. First, simply being affiliated with the same

governmental body does not strengthen the connection between two NIs because the construction of NIs involves not only the government but also other stakeholders, such as sponsors and construction contractors. Additionally, the steady construction of NIs requires a comprehensive study and judgment. Second, it is challenging to form synergy among NI projects because of the obstacles in coordinating information and resources among government departments. Li found that the urban sectors were not a pure driver of collaborations among actors, and the formation of collaboration is attributable to homophily effects rather than organizational closeness [52]. Therefore, when considering how to maximize the effectiveness of NIs, we should also focus on improving the coordination between management departments and opening up NI development channels from top to bottom. In addition, geographical proximity does not increase the association of information transfer, resource sharing, and collaboration among the NIs in Chongqing. Geographical homophily means the spatial clustering of resources, but Geldes et al. found that geographical proximity played no significant role in promoting innovative cooperation between organizations. Instead, cognitive and technological proximity were more likely to generate innovation [72]. Therefore, building NIs in proximity would maximize synergy when there are already good partnerships among them.

6. Conclusions

This study constructed a network based on the interactions among New Infrastructure (NI) projects in Chongqing and adopted social network analysis to explore the overall characteristics of the interdependency network among the projects. An exponential random graph model (ERGM) was used to reveal the formation mechanism of this network. The influences of node attribute variables, homophily variables, and network structure variables on the entire interdependency network were comprehensively examined with the aim to provide suggestions for the construction of Nis in Chongqing. The following conclusions can be drawn:

(1) In Chongqing's NIs, information infrastructures for 5G, big data, cloud computing, and other technologies are the critical nodes in Chongqing's NI interdependency network. Such NIs occupy favorable positions with more significant influences on resource mobilization and information exchange, so Chongqing's government should place the construction and improvement of information infrastructures in advanced strategic positions. (2) To maximize the value of NI projects in Chongqing, the government must efficiently coordinate information and resources. (3) The network of NI projects in Chongqing is characterized by "reciprocity" and "small group", which can be used to aggregate the NIs with such characteristics in project design to create an agglomerating effect and promote the utility of each NI. (4) When planning an NI project, the project's own functional and interactive characteristics should be taken into account, its management should be effectively coordinated, and the best location for the project should be determined. As the vision of infrastructure investment gradually turns from traditional infrastructures to NIs based on new technologies, the continuous increases in investment and construction should be complemented by more scientific and reasonable construction layouts and planning. This study contributes to infrastructure research in several ways. First, we extend the existing literature on infrastructure interdependence. NIs are essential for society's transformation to be digital, networked, and intelligent. They also play critical roles in the evolution of urban spatial distribution patterns. Decision-making for construction, investment strategies, and cross-sector cooperation can be facilitated with the support of a study of the interactions between NIs. There are currently plenty of studies on the interactions between traditional critical infrastructures [73,74], but not as enough on NIs, which encourage blind investment, duplication, and inefficiency in decision-making about NIs. Our study complements the literature in this field. Second, SNA and the ERGM were combined in this study, with a focus on the NI's overall network structure, the interactions among network variables, and the process of network development. There were limitations to previous studies using only

SNA or regression models. SNA ignored connections beyond the actors [12]. In reality, the node attributes, homophily, and network structure of the NIs also have an effect on the network in addition to the actors' interactions. The regression model assumes that actors are independent of one another [13]; however, the NIs are actually interdependent rather than independent of one another. These issues can be addressed with a combination of SNA and the ERGM. Based on the reality of interdependence among NIs, we focused on the impact of factors other than actors (e.g., node attributes, homophily, and network structure) on NI networks. Third, we can provide more detailed guidance on the sequencing of NIs to be constructed, the investment priorities, and how sectors might collaborate by analyzing the interactions between network variables and formation mechanisms. We can identify the most critical and influential nodes in the NI network by exploring the overall network structure. As a result, we can prioritize the construction order of such NIs and increase the scale of investment, which is beneficial to decision-making on NI construction, function performance, and investment efficiency. Furthermore, some NIs have strong links, and their cooperation can promote the respective functions and create synergy. As a result of their management departments' collaboration, information and resource exchange channels can be opened, allowing the benefits of cooperation to be expanded even further. This idea can also be applied to determining the location of NIs. The NIs with reciprocities and transitivities can be built in proximity to boost the clustering effects, making it easier for both sides to function and contribute to the decision-making of NIs. There are some shortcomings in this study. There are still many NIs under construction in Chongqing and only those NIs that have been completed were selected. The network could be expanded as the number of NIs increases and the correlations between nodes can be identified with the help of big data analysis to make future research more scientific and objective. In addition, this study constructed an interdependency network based wholly on NIs, but the actual current operations of the NIs are also linked to the traditional infrastructures. There are also unobserved linkages between the various infrastructures, so established infrastructures could be added to the interdependency network to aid in the finding of infrastructure linkages in order to better advise on decisions regarding urban infrastructure development.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/buildings12070937/s1, Table S1: Chongqing new infrastructure classification and subordinate department code table, S2: ERGM model specific construction process.

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