ISSN 1392-3730/eISSN 1822-3605

JOURNAL of CIVIL ENGINEERING and MANAGEMENT

2025
Volume 31
Issue 2
Pages 97–112
https://doi.org/10.3846/jcem.2025.23017

HOW DOES THE COLLABORATIVE INNOVATION NETWORK IN CONSTRUCTION INDUSTRY EVOLVE? EVIDENCE FROM CHINA

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Article History:
- received 11 March 2024
- accepted 15 August 2024

Abstract. Technology innovation in the construction industry involves collaboration among multiple innovation organizations which formed an intricate collaborative innovation network (CIN). To understand the evolution characteristics of structural characteristics of CIN in China's construction industry and to clarify the collaborative patterns among innovation organizations, the CIN were analyzed in terms of overall network characteristics and local collaborative patterns by using the social network analysis (SNA) and network motif analysis (NMA), respectively based on the data of projects winning the China's Science and Technology Award in Construction (CSTAC) in 2004–2021. The results indicate that the CIN became larger but less connected and exhibited scale-free and small-world characteristics during the study period. There is a giant component in the CIN, which is gradually increasing in size and becoming more cohesive. China Academy of Building Research which had the highest degree centrality and closeness centrality and Tongji University which had the largest betweenness centrality had an important position in CIN. The main collaborative innovation mode in China's construction industry is collaboration between enterprises, followed by collaboration between enterprise-university, which has an increasing share. The results help organizations clarify their position in the CIN and inform their development of co-innovation partners.

Keywords: collaborative innovation network, technology innovation, social network analysis, network motif analysis, dynamic evolution, collaborative pattern, construction industry.

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1. Introduction

As one of China's traditional industries, the construction industry has been relying on resource inputs to drive development for many years, with a low level of industrialization and informatization. Currently, China's construction industry is actively implanting the strategy of innovation-driven development, i.e., innovation to promote technological progress and industry transformation. Technology innovation in the construction industry often involves multiple professional fields and requires multiple resources, making it challenging to accomplish by only one organization. Collaborative innovation theory suggests that collaboration can facilitate knowledge integration among innovation organizations and reduce innovation costs, thereby improving innovation efficiency (De Noni et al., 2018). Due to the one-time nature of technology innovation projects, an innovation organization will continuously establish new collaborative relationships with other organizations based on new technology innovation projects. During the implementation of many technology innovation projects in the construction industry, these innovation organizations have gradually formed an intricate collaborative innovation network (CIN) connected by technologies (Han et al., 2018).

The CIN in the construction industry involves the vertical collaborative relationship between an innovation enterprise and its upstream suppliers and downstream users. It also involves the horizontal collaborative relationship between an innovation enterprise and the government, universities, and research institutes. With the increase in technology innovation activities, the collaborative relationships in the CIN are constantly changing and affecting the performance of technology innovation (Zhao & Li, 2022). An in-depth exploration of the structural characteristics of the CIN and their changes in the construction industry can help innovation organizations clarify their positions in the CIN and provide references for choosing innovation partners and better integrating into the CIN. Furthermore, it also can help managers understand the collaborative patterns among technology innovation organizations, identify the core organizations that lead the industry's technology progress, and provide a basis for formulating technology innovation policy for the construction industry.

Currently, most of the research on CIN focuses on high-tech industries or emerging industries (Wang et al., 2023a; Yu et al., 2023). As a traditional industry, the CIN of the construction industry lacks attention. As for the studies of technology innovation in the construction industry, scholars primarily focused on the invention and application of new technologies (Wang et al., 2022; Yu, 2023). There is a lack of exploration of the relationship network formed by the many innovation organizations in their intertwined collaborations at the industry level. What are the structural characteristics of CIN in China's construction industry? How have the collaborative relationships and collaborative patterns of organizations in CIN evolved? Which innovation organizations drove technology innovation in China's construction industry? This study focuses on the above issues of CIN in the construction industry to fill the knowledge gap.

Social network analysis (SNA) is an approach that combines graph theory and mathematical modeling to uncover the macrostructural characteristics of complex networks (Shen & Xue, 2023). As a subgroup structure analysis method, network motif analysis (NMA) can help identify the local topology to reveal the microstructural characteristics of complex networks (Wang et al., 2023b). Combining SNA and NMA helps capture the global and local characteristics of a network. This study combines SNA and NMA methods to investigate the characteristics and evolution of CIN formed by collaborative innovation organizations that won the China's Science and Technology Award in Construction (CSTAC) from 2004 to 2021 in terms of macroscopic overall network and microscopic local structure.

The rest of this paper is organized as follows. The literature on technology innovation in the construction industry and collaboration networks in technology innovation is reviewed in Section 2. Section 3 introduces the research methods and data sources. Section 4 presents the results and discussion, including the analysis of the structural characteristics and dynamic evolution of CIN in China's construction industry, and collaborative patterns among innovation organizations. Section 5 summarizes the results and proposes the managerial implications.

2. Literature review

2.1. Studies of technology innovation in the construction industry

Scholars have made some attempts to study technology innovation in the construction industry. Some have studied the invention and application of new technologies (Zhao & Cheah, 2023) and new materials (Alsomiri et al., 2023) from the technology perspective. Some have evaluated the technology innovation capacity of regional construction industries or construction enterprises. For example, Dou et al. (2021) evaluated the technology innovation competence of six prefabricated building construction companies in China. Van Wyk et al. (2024) analyzed the adoption of new technologies in the South African construction industry through a questionnaire survey. Some scholars have also measured the technology innovation efficiency of the construction industry from an input-output perspective. For example, Wang et al. (2023c) measured the green technology innovation efficiency of China's construction industry. Cheng et al. (2023) evaluated the technology innovation efficiency of listed construction enterprises in China.

In summary, the above literature has studied the technology innovation in the construction industry from different aspects. Research on new technology inventions presents the technology innovation achievements, and research on the technology innovation level helps to understand the overall development status of technology innovation. The generation of technology innovation achievements and the improvement of technology innovation level involve the efforts of mutual collaboration between innovation organizations. However, the collaborative relationships among innovation organizations in the construction industry have not yet been revealed. Understanding the relationship between innovation organizations can clarify the innovation mode of the construction industry and provide a guiding direction for innovation organizations to perform collaborative innovation in the future. Therefore, further research is urgently needed on the collaborative relationship among technology innovation organizations in the construction industry.

2.2. Studies of collaborative innovation network (CIN)

Innovation organizations often form a complex CIN because of numerous innovation collaborations. The SNA method can be applied to sightsee the characteristics of complex networks. Therefore, scholars have used SNA to study the CIN in different fields, including manufacturing, energy, and information and communication. For example, Li et al. (2021) found that the scale of CIN in China's smart manufacturing equipment industry became larger over the study period and was characterized as a small-world network. Liu et al. (2023) found that the CIN in China's smart grid field had different characteristics at different stages, but the State Grid Corporation of China was always at the core of the network. Hwang (2023) found that CIN in the information and communication technologies industry in Korea exhibited poor connectivity and scale-free properties. Liu et al. (2024) constructed a CIN for the energy conservation and environmental protection industry and found that the network had a low density and a fragmented structure.

With the flow of innovation elements, cross-industry exchanges among innovation organizations have gradually increased, leading to the formation of cross-industry CIN. Some scholars have focused on CIN across industries. For example, König et al. (2011) constructed a knowledge exchange network formed among firms in different industries and found that the network contained highly interconnected clusters of firms. Tomasello et al. (2017) investigated the dynamic evolutionary characteristics of the CIN formed among different R&D sectors in 1986–2009, demonstrating that the network presented a core-periphery structure, small-world characteristics, and scale-free properties over time.

Besides, CIN at the city, regional and national level have also attracted the attention of scholars. Graf (2011) constructed a CIN for four regions in East Germany based on patent data and found that public research institutes acted as gatekeepers more often than private sectors. In the study of co-invention networks involving 331 cities in the United States, Breschi and Lenzi (2016) found that a high social proximity degree between two innovation organizations can facilitate the rapid diffusion of knowledge and that the emergence of small groups enables cities to achieve greater inventive creativity. Andersson et al. (2019) analyzed the structural characteristics of CIN in Spanish and Swedish, finding that the CIN in Spanish exhibited good connectivity, whereas the CIN in Swedish demonstrated high density. Galaso and Kovarik (2021) demonstrated that geographic boundaries led to varying effects of CIN on future innovation by examining how CIN influences innovation in Spain and its three regions. Hu et al. (2024b) argued the increasing accessibility of global innovation networks, exhibiting scale-free properties and four clustered subgroups from 1999 to 2020. Previous studies suggested that there were differences in the structural characteristics of the CIN in different fields. Currently, there is a lack of research on CIN in the construction industry. The structural characteristics of CIN in the construction industry are still unclear and need to be further explored.

Although SNA has been widely used in investigating the structural characteristics of the CIN, it can only reveal the macrostructural characteristics of the overall network. The characteristics of the overall network are usually dominated by some small subgroup structures called network motifs (Stone et al., 2019). Unlike SNA, NMA can be used to reveal the microstructural characteristics of subgroups and local topological structure of network, thereby determining the key connectivity patterns in the network. Recently, NMA methods have also been gradually introduced by scholars from biology to network studies in the transportation field (Shen et al., 2022), the energy industry (Pu et al., 2021), and the agriculture industry (Tavella et al., 2022).

SNA can be applied to analyze the overall structural characteristics of the network, and NMA helps reveal the features of local network structure. Therefore, we combined SNA and NMA to develop a new framework for network structure analysis to explain the characteristics of the CIN and patterns of inter-organizational collaborative innovation in the construction industry.

3. Methodology

3.1. Social network analysis

SNA is a method used to analyze social structures based on mathematical modeling and graph theory. It is widely used to study the connections and relationships between individuals, organizations, or other entities within a network (De Iudicibus et al., 2024; Hu et al., 2024a). The SNA method employs quantitative metrics to delineate the relationship of nodes in a network and can reveal the structural features of the overall network and the positional attributes of nodes at the network level and node level, respectively (Wang et al., 2020). Table 1 lists the formulas for the SNA metrics in this study.

The metrics at the network level include network density, degree distribution, average clustering coefficient, average path length, and community discovery. (i) Network density is the ratio of the number of actual linkages to the possible linkages in the network, and can reflect the connectivity of the network (Wang et al., 2020). (ii) Degree distribution describes the probability distribution of degrees of nodes in a network and the degree of a node refers to the count of nodes directly linked to that node. Degree distribution can be used to identify the scale-free characteristics of the network (Han et al., 2018). The scale-free is a structural characteristic of complex networks in which most nodes have only a small number of connections, while a few nodes have many connections (Barabási & Bonabeau, 2003). A network exhibits the scale-free characteristic if the degree distribution of the network nodes follows the power law distribution. (iii) The average clustering coefficient is the mean of the clustering coefficients of all nodes in the network, in which the clustering coefficient of a node is the ratio of the actual number of linkages among this node and its neighbors to the maximum possible number of linkages among those nodes. The average clustering coefficient reflects the agglomeration of the network (Qiang et al., 2021). (iv) The average path length is the average of the shortest path lengths between all nodes and it reflects the transportability of the network (Mao & Zhang, 2017). The shortest path length between any two nodes is the minimum number of edges to go through from one node to the other. The network is a small-world network if it has a high average clustering coefficient and a low average path length (Wang & Chen, 2003). (v) Complex networks naturally segregate into many communities, often characterized by tightly connected nodes with sparse connections to the nodes of other groups (Steinhaeuser & Chawla, 2010). Community discovery helps to discover clustered groups. In this study, the heuristic algorithm based on modularity optimization (HAMO) is used for community discovery computation due to its advantages of short computation time and high quality of community delineation. Modularity ranges from –1 to 1. The larger the value of modularity, the better the quality of community delineation (Newman, 2006).

Table 1. Calculation formula of SNA

Indicator	Formula	Explanation of parameters
Network Density	$ND = \frac{2L}{N(N-1)}$	L – the number of linkages in the network N – the number of nodes in the network
Degree Distribution	$P(k) = \frac{N_k}{N}$	N_k – the number of nodes with degree k
Average Clustering Coefficient	$ACC = \frac{1}{N}\sum_{i=1}^{N}\frac{2l_i}{k_i(k_i-1)}$	k_i – the number of neighbors of the node i l_i – the number of linkages among the node i and its neighbors
Average Path Length	$APL = \frac{1}{N(N+1)/2}\sum_{i\geq j} d_{ij}$	d_{ij} – the shortest path length between the node i and the node j
Modularity	$Q = \frac{1}{2L}\sum_{i,j}\left[A_{ij} - \frac{e_i e_j}{2L}\right]\delta(c_i, c_j)$	A_{ij} – if there's a linkage between the node i and the node j, then A_{ij} = 1; otherwise A_{ij} = 0 e_i – the number of direct linkages of node i e_j – the number of direct linkages of node j c_i – the community to which node i belongs c_j – the community to which node j belongs $\delta(c_i, c_j)$ – if c_i and c_j are the same community, then $\delta(c_i, c_j)$ = 1; otherwise $\delta(c_i, c_j)$ = 0
Degree Centrality	$DC_i = \frac{\sum_{j=1}^{N} l_{i,j}}{N-1}$	$l_{i,j}$ – the number of linkages between the node i and the node j
Betweenness Centrality	$BC_i = \sum_{j<k}\frac{g_{jk}(i)}{g_{jk}} / \frac{(N-1)(N-2)}{2}$	g_{jk} – the number of the shortest path from node j to node k $g_{jk}(i)$ – the number of shortest paths from node j to node k that pass through node i
Closeness Centrality	$CC_i = \frac{N-1}{\sum_{j}^{N} d_{ij}}$	

The metrics at the node level include degree centrality, betweenness centrality, and closeness centrality. (i) Degree centrality is the total number of direct linkages a node has, reflecting the extent of direct communication the node has in the network (Lu et al., 2021). A node with a large degree centrality has many collaborative relationships and is central to the network. (ii) The betweenness centrality of a node is determined by the count of the shortest paths through that node. It can reflect the mediating and bridging role that a node plays in the network (Shen & Xue, 2023). (iii) Closeness centrality of a node is the inverse of the shortest path length of that node to all other nodes in the network, reflecting the proximity of a node to other nodes (Wang et al., 2020).

3.2. Network motif analysis

Network motifs are some small linked subgroups with 3–7 nodes occurring in actual networks at numbers that are more than those in randomized networks (Park & Zhong, 2022). In contrast, network antimotifs are also subgroups in the real network, but their presence is lower than that in random networks of the same size (Milo et al., 2002). As an indicator of statistical significance, Z-Score is commonly applied to evaluate the importance of different types of network motif structures in a network (Milo et al., 2004). The Z-Score of the subgroup is defined as follows:

$$Z_i = \frac{N_{real_i} - N_{rand_i}}{\sigma_{rand_i}}, \tag{1}$$

where N_{real_i} denotes the count of appearances of subgroup i in the CIN, N_{rand_i} is the average number of appearances of subgroup i in the random network iterated, and σ_{rand_i} is the standard deviation of the count of subgroup i in the random network. $Z_i > 0$ means that the count of appearances of subgroup i in the real network is more than that in the random network and subgroup i is defined as the network motif. $Z_i < 0$ means that the count of appearances of subgroup i in the real network is less than that in the random network and subgroup i is thus defined as the network antimotif (Milo et al., 2002). Motifs appear frequently in networks, and they have a greater impact on the evolution and development of networks compared to antimotif.

3.3. Data collection

According to Roberts (2007), innovation refers to the creation of new technological outcomes and knowledge, and their application to engineering activities. Therefore, we measured innovation based on technological outcomes generated during the implementation of engineering projects rather than patents. CSTAC is an award established to promote scientific and technological innovation in China's construction industry. The awarded projects are generally excellent scientific and technological achievements regarding new technologies, new construction methods, and new materials. These projects must meet the following criteria: (1) demonstrating significant innovations in technology and methodology and addressing substantial technical challenges; (2) generating considerable economic, social, and environmental benefits; and (3) achieving a high level of transformation of the outcomes, with a substantial demonstration effect and high promotion and application value. Therefore, the CSTAC can reflect the level of technological innovation in China's construction industry.

CSTAC participants must be groups rather than individuals. This group includes enterprises, universities, research institutes, government departments and industry associations. A joint application for CSTAC requires an equal partnership among the organizations. Therefore, each CSTAC achievement is usually a collaborative effort of multiple innovation organizations, including enterprises, university, research institute, government department, and industry association.

CSTAC selection began in 2003 and has been held annually since then. Since many of the organizations awarded in 2003 have been written off, we chose 2004–2021 as the study period. The required data were obtained from the official website of the Technology and Industrialization Development Center of the Ministry of Housing and Urban Rural Development of China (http://www.cstid.org.cn/) and the China National Knowledge Infrastructure (www.cnki.net). A total of 2,106 projects that were awarded CSTAC during the study period were obtained. Two awarded projects in this study were removed because all the organizations they involved were written off. Therefore, the final dataset contains 2,104 projects that received CSTAC from 2004–2021.

The data is processed according to the following rules. First, deregistered organizations are removed, and organizations that have been renamed use the latest names. Second, for some enterprises with multilevel subsidiaries, only the head office, first-tier subsidiaries, and second-tier subsidiaries are considered as nodes in the network. Third, we regarded universities involved in technological innovation rather than their affiliated colleges as nodes. Fourth, participating organizations are classified based on their attributes as enterprises, universities, research institutions, government departments, and social organizations. In the end, 2,104 projects involved a total of 2,449 innovation organizations.

Table 2 shows the number of award-winning organizations of different types. It can be seen that enterprises have the largest share, the number of social organizations is relatively small, and the number of universities, research institutes and government departments is gradually increasing.

4. Results and discussion

4.1. Network topology

We divided the study period into six periods, namely 2004–2006, 2007–2009, 2010–2012, 2013–2015, 2016–2018, and 2019–2021. Since the collaboration between innovation organizations is mutual, the CIN is an undirected unweighted network. To construct the CIN, an adjacency matrix is first constructed based on whether there is a collaborative relationship between organizations. Each element of the adjacency matrix has a value of 1 or 0, where 1 and 0 indicate the existence and non-existence of collaborative relationship between two organizations, respectively. Accordingly, six adjacency matrices were constructed as 330×330, 388×388, 567×567, 627×627, 636×636, and 1011×1011, respectively.

Based on the constructed six adjacency matrices, we used Gephi software to generate the network topology shown in Figure 1. The nodes in Figure 1 represent innovation organizations and the size of a node reflects how many nodes are directly connected to it. The more organizations collaborate with a node, the larger that node is. Different types of organizations are represented by diverse colors and letters. Blue nodes denote enterprises, represented by "E". Universities are denoted by "U" and are red nodes.

Table 2. Number of organizations winning CSTAC in 2004–2021

Year	Enterprise	University	Research Institute	Government	Social Group	Total
2004	79	19	11	13	3	125
2005	86	18	18	24	1	147
2006	78	21	14	18	7	138
2007	105	24	19	17	3	168
2008	95	25	19	15	0	154
2009	104	23	19	16	1	163
2010	114	23	31	17	6	191
2011	142	29	33	16	2	222
2012	185	37	29	30	1	282
2013	168	33	22	20	0	243
2014	174	37	30	26	1	268
2015	170	31	33	19	4	257
2016	157	32	28	19	1	237
2017	177	37	22	20	3	259
2018	224	39	29	20	1	313
2019	206	46	18	21	3	294
2020	392	52	33	36	4	517
2021	358	51	36	24	1	470

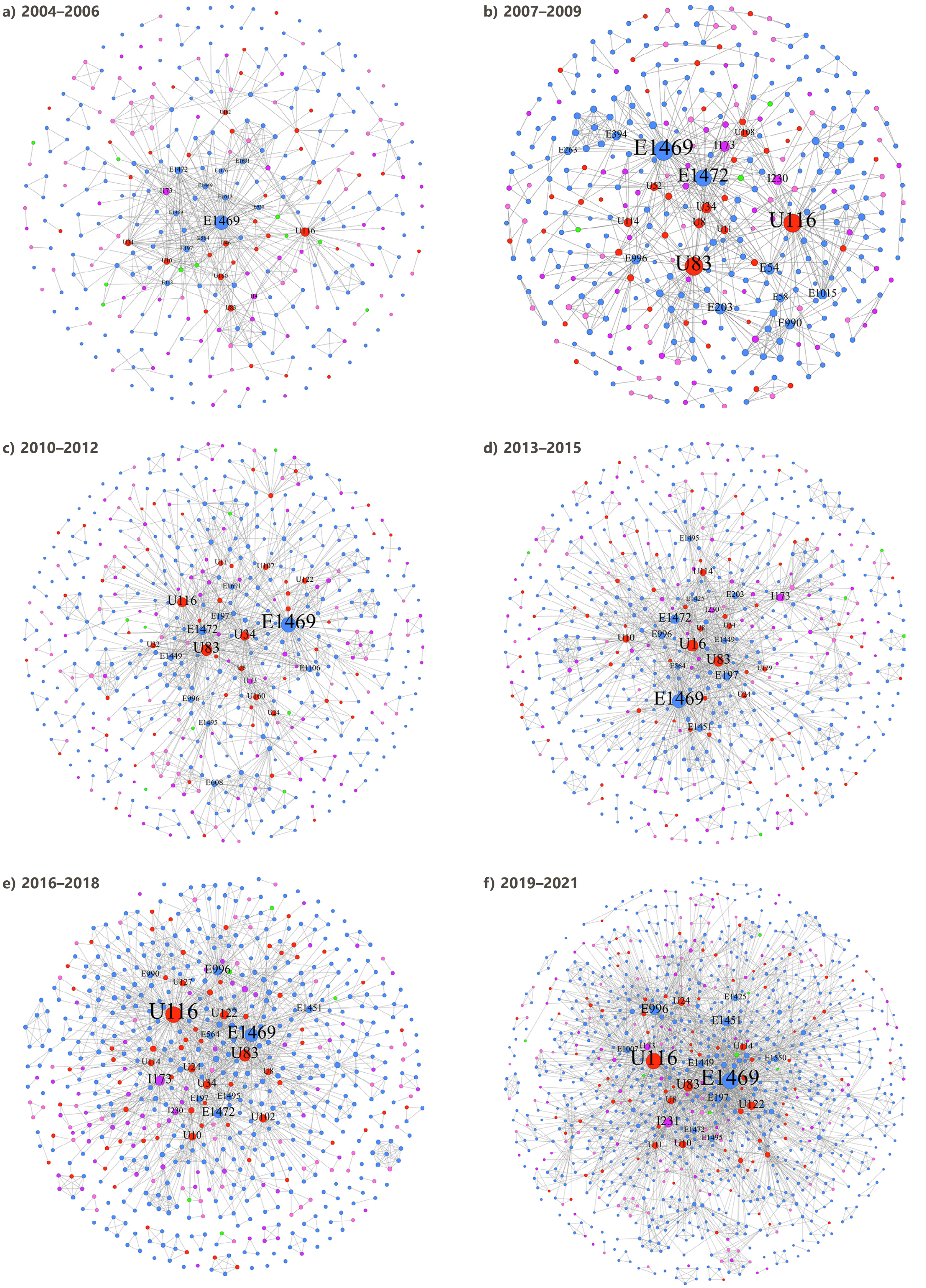


Figure 1. The network topology at six time periods

"I" represents the research institutes, which are presented as purple nodes. Green nodes represent social organizations, mainly industry associations, and are denoted by "S". Governments are represented by pink nodes with the letter "G." As can be seen that the size of CIN became larger and the network structure became more complex over time. It indicates that technology innovation in the construction industry involves more and more innovation organizations and the collaborative relationships among innovation organizations have become increasingly complex.

4.2. Network-level analysis

(1) Change of the network structural characteristics

Table 3 shows the results of the network metrics at six time periods. The following findings can be drawn: (i) The network density at six time periods was low, implying poor connectivity of the network. Although some organizations in large innovation groups communicated frequently with each other, there was less communication between groups. Such island effect led to low network connectivity. Dou and Bo (2022) study suggested that building information model (BIM) patent collaboration networks in China were also characterized by poor connectivity. (ii) The average clustering coefficients of the networks were greater than 0.850, indicating that the networks were well clustered. (iii) The values of average path length were all between 3 and 4, indicating that any two innovation organizations were connected through four innovation organizations on average.

(2) Analysis of the network scale-free property

The degree distribution of the nodes can be used to specify the scale-free properties of the network. The node degree distribution of the CIN was fitted and a Kolmogorov-Smirnov test was performed. First, the node degree distribution of the CIN in double logarithmic axes were plotted. Then, a power function was used to fit the scatterplot of the node degree distribution. The results are shown in Figure 2. According to Barabási and Albert (1999), a straight line and R^2 greater than 0.7 for the fitted curve of the node degree distribution in a double logarithmic coordinate system implies that the degree distribution conforms to a power law distribution. According to Figure 2, the node degree distribution of CIN exhibits power law distribution at six time points. In a complex network, the node degree conforming to a power law distribution implies that the network exhibits scale-free characteristics. Therefore, the result suggests the scale-free characteristic of the investigated CIN. Finally, a Kolmogorov-Smirnov test is executed on the node degree distribution of the CIN. The p-values of the Kolmogorov-Smirnov statistic (0.999, 0.887, 0.993, 0.946, 0.989, and 0.957, respectively) are all greater than 0.1 (Clauset et al., 2009), implying that the nodal degree of the CIN follows a power-law distribution. It indicates that a few organizations have many collaborative relationships with other organizations due to their strong innovative capabilities or rich innovative resources, while most organizations have few connections with other organizations. Yu et al. (2022) found that the CIN of China's fly ash utilization technology also exhibited obvious scale-free characteristics.

(3) Analysis of the network small-world property

The small-world network, proposed by Watts and Strogatz (1998), refer to a type of network that is intermediate between regular and random networks, characterized by local clustering and overall connectivity. The small-world network is characterized by high clustering coefficients and low average path lengths (Wang & Chen, 2003). In a small-world network, communication and interaction among organizations are frequent, and information is transmitted quickly. Typically, the average clustering coefficient in the empirical network is greater than the network density, implying that it has a high average clustering coefficient. The average path length in the empirical network is less than that of the random network, implying that it has a low average path length (Neal, 2018). The 1000 random networks with identical number of nodes and network density as the constructed CIN are generated in six time periods, respectively. The average path lengths of random networks in six time periods are 4.210, 4.308, 4.068, 3.990, 3.987, 3.807, and 3.753, respectively. As can be seen from Table 3, the average clustering coefficient is always larger than the network density in six time periods. The CIN in the construction industry has smaller average path lengths than that of the random network. Therefore, the CIN of the construction industry presents small-world characteristics, which is conducive to communication and technology diffusion among innovation organizations.

Table 3. Results of network level analysis for six time periods

Indicator	2004–2006	2007–2009	2010–2012	2013–2015	2016–2018	2019–2021
Number of Nodes	330	388	567	627	636	1011
Linkages	685	822	1442	1675	1928	3569
Density	0.0126	0.0109	0.009	0.0086	0.0095	0.007
Average Clustering Coefficient	0.858	0.866	0.875	0.884	0.865	0.865
Average Path Length	3.240	3.193	3.431	3.251	3.304	3.406
Modularity	0.667	0.716	0.721	0.676	0.647	0.644
Number of Community	87	84	95	98	73	70

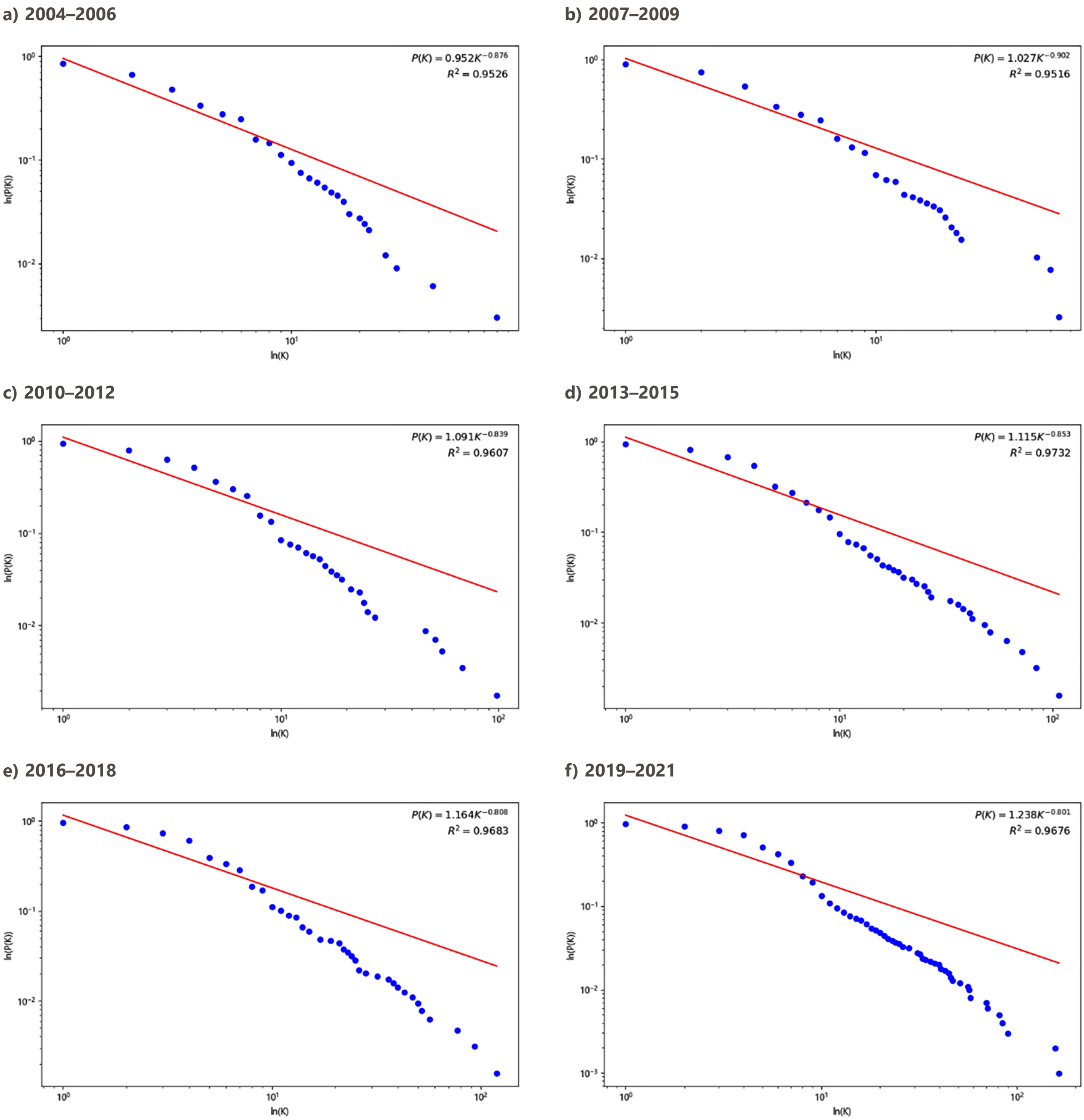


Figure 2. Power-law distribution of node degrees in the network in six time periods

(4) Analysis of the network community discovery

We used HAMO to discover the community structure in the network. Clauset et al. (2004) stated there was an obvious community in the network when the modularity of a network was greater than 0.7. Table 3 shows that the modularity values of the CIN had been around 0.7. Thus, the CIN of China's construction industry had a distinct community structure.

As can be seen in Table 3, the number of communities in the network decreased during the study period. Since the total number of nodes in the network has increased, the drop in the number of communities indicates that some communities have involved more innovation organizations, i.e., the community size became larger. Such finding is different from that of Pu et al. (2022) on the CIN of lithium-ion batteries. Pu et al. (2022) found that the communities of the lithium-ion battery CIN increased over time, no core communities emerged and most of the communities were small. Differences in industry attributes lead to differences in results. Compared to the construction industry, R&D projects for lithium-ion battery technology involve fewer organizations, and therefore no large communities have formed. In the construction industry, the R&D of some technologies is difficult and relies on the collaboration of many innovation organizations. For example, the Hong Kong-Zhuhai-Macao Bridge construction project in China created about 64 new technologies during the construction process from 2009 to 2018, involving about 200 innovation organizations. Recently, China has been actively promoting the industrialization of construction, intelligent construction, and green construction, generating demand for R&D of many new technologies. Many enterprises and research institutes have been collaborating in the R&D of these new technologies, forming several large innovation communities.

(5) Analysis of the giant component

Figure 1 shows that there is a giant component in the CIN of China's construction industry. The relative size, network density, average clustering coefficient, and average path length of the giant component were calculated, and the results are presented in Table 4. The relative size of a giant component is defined as the ratio of the number of nodes it contains to the total number of nodes in the entire network. The relative size of giant component has generally increased over time, indicating a gradually collaborative innovation community among organizations in the construction industry. The decrease in network density suggests that, despite the existence of a large innovation community in the construction industry, the collaborative connections among innovation organizations in the community are becoming increasingly sparse. This is due to the number of relationships formed by newly embedded organizations in the CIN being greater than those formed between the original organizations in the CIN. The average clustering coefficient exhibits a fluctuating growth trend, indicating that the overall cohesion of the giant component has increased. According to Figure 1, clustering subgroups centered on Tongji University (U116), Tsinghua University (U83), and China Academy of Building Research (E1469) have emerged in the giant component. The average path length for the giant component remained between 3 and 4 during the study period, indicating that communication among innovation organizations in the construction industry conforms to the "four degrees of separation". In other words, any two innovation organizations need to connect through only four intermediaries to establish a collaborative relationship in a fully connected innovation community. The low average path length among innovation organizations facilitates the rapid diffusion of new knowledge, technologies, and resources in the construction industry.

4.3. Node-level analysis

(1) Analysis of degree centrality

Degree centrality characterizes the position of nodes in the network. The greater the degree centrality of a node, the more influential it is in the network. It helps to reveal the organizations that drive technology innovation in the construction industry. Table 5 lists the top 5 organizations in terms of degree centrality. It shows that the degree centrality of China Academy of Building Research (E1469) has been in the top 2 during the study period, i.e., E1469 has been at the core of the CIN. E1469 is the largest comprehensive R&D organization in China's construction industry,

Table 4. Results of the network indicator for the giant component for six time periods

Indicator	2004–2006	2007–2009	2000–2012	2013–2015	2016–2018	2019–2021
Relative size	63.64%	63.92%	72.49%	69.70%	78.93%	89.02%
Density	0.028	0.024	0.016	0.016	0.014	0.009
Average Clustering Coefficient	0.837	0.853	0.869	0.866	0.847	0.858
Average Path Length	3.247	3.201	3.434	3.256	3.306	3.407

Table 5. Top 5 organizations in degree centrality

No.	2004–2006	2007–2009	2010–2012	2013–2015	2016–2018	2019–2021
1	China Academy of Building Research	China Academy of Building Research	China Academy of Building Research	China Academy of Building Research	Tongji University	China Academy of Building Research
2	Tongji University	Tongji University	Tsinghua University	Tongji University	China Academy of Building Research	Tongji University
3	China Architecture Design & Research Group	Tsinghua University	Tongji University	Tsinghua University	Tsinghua University	Tsinghua University
4	China Academy of Urban Planning & Design	China Architecture Design & Research Group	Harbin Institute of Technology	China Architecture Design & Research Group	China Academy of Urban Planning & Design	Shanghai Research Institute of Building Sciences Co., Ltd
5	Tsinghua University	Beijing Urban Construction Group Co., Ltd	China Architecture Design & Research Group	Beijing Institute of Architectural Design Co., Ltd	China Architecture Design & Research Group	Technology and Industrialization Development Center of the Ministry of Housing and Urban Rural Development

with research areas covering a wide range of areas such as building structure, construction technology, and building materials. E1469 has sufficient funds, excellent talents, and advanced R&D laboratories, which have enabled it to create abundant scientific and technological achievements. From 2004 to 2021, E1469 has won 237 CSTAC, thus occupying a core position in the CIN. Besides, the degree centrality of Tongji University (U116) has always been ranked in the top three and increased from 0.128 in 2006 to 0.155 in 2021, indicating an increase in its core position in the network. U116 is strong in the discipline of civil engineering, with several key laboratories and many experts, which lays a solid foundation for its technology innovation. In 2004–2021, U116 has won 159 CSTAC.

(2) Analysis of betweenness centrality

The betweenness centrality reflects the mediating role of innovation organizations in a CIN. The top 5 organizations in terms of betweenness centrality are summarized in Table 6. According to Table 6, Tongji University (U116) and China Academy of Building Research (E1469) have been in the top two in terms of betweenness centrality. During the study period, the betweenness centrality of E1469 decreased, while that of U116 increased, indicating that the intermediary role of U116 in CIN has become more and more significant. Han's et al. (2018) study on CIN in the construction industry also suggested that universities played a significant intermediary role in technology innovation. New construction technologies always involve interdisciplinary knowledge. Universities are important carriers of knowledge dissemination and have the advantage of interdisciplinary collaboration in R&D. As a well-known university in the civil engineering field, U116 has collaborated with different organizations for technology innovation projects. Besides, U116 has established technology innovation alliances with many institutions through its active advocacy. Therefore, U116 played a bridge role in the collaboration of innovation organizations in the construction industry.

(3) Analysis of closeness centrality

Closeness centrality reflects how close a node is to other nodes in a network and its importance in the network (Liu et al., 2021a). According to Table 7, China Academy of Building Research (E1469), Tongji University (U116), and Tsinghua University (U83) consistently ranked in the top three in terms of closeness centrality. The high closeness centrality indicates that they have established collaborative innovation relationships with many organizations in the network and they are important organizations for promoting technological innovation in China's construction industry.

4.4. Collaborative patterns

Next, we used NMA to further explore the local structural characteristics of CIN at the micro level. NMA is to discover motifs and antimotifs in the network through iterative calculation. In the CIN of the construction industry, the subgroup structure belonging to the network motif is a localized collaborative pattern that has a high impact on the network.

Figure 1 shows that the number of isolated nodes gradually decreased and that of linked nodes gradually increased, which indicates an increasing collaboration among innovation organizations. We eliminated isolated nodes and performed NMA on CIN containing only linked nodes to explore the subgroup structure and collaborative patterns among innovation organizations.

Barabási and Oltvai (2004) found experimentally that 3-node and 4-node subgroups were the main subgroup structures in complex networks. The data of CSTAC also showed that most of the awarded projects were completed jointly by three or four innovation organizations. Therefore, we mainly discussed the 3-node and 4-node subgroups in CIN. The 3-node and 4-node subgroups are discovered using the Mfinder 1.20 software. Specifically, we used the switching method to generate 1000 random networks with the same number of nodes and edges as the CIN.

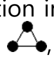
Table 6. Top 5 organizations in betweenness centrality

No.	2004–2006	2007–2009	2010–2012	2013–2015	2016–2018	2019–2021
1	China Academy of Building Research	Tongji University	China Academy of Building Research	Tongji University	Tongji University	Tongji University
2	Tongji University	Tsinghua University	Tongji University	China Academy of Building Research	China Academy of Building Research	China Academy of Building Research
3	China Academy of Urban Planning & Design	China Academy of Building Research	Tsinghua University	Tsinghua University	Tsinghua University	Tsinghua University
4	China Architecture Design & Research Group	China Architecture Design & Research Group	Harbin Institute of Technology	China Academy of Urban Planning & Design	China Academy of Urban Planning & Design	Technology and Industrialization Development Center of the Ministry of Housing and Urban Rural Development
5	Shenyang Jianzhu University	Shanghai Research Institute of Building Sciences Co., Ltd	China Architecture Design & Research Group	China Architecture Design & Research Group	Shanghai Research Institute of Building Sciences Co., Ltd	Shanghai Research Institute of Building Sciences Co., Ltd

Table 7. Top 5 organizations in closeness centrality

No.	2004–2006	2007–2009	2010–2012	2013–2015	2016–2018	2019–2021
1	China Academy of Building Research	Tsinghua University	China Academy of Building Research	Tongji University	China Academy of Building Research	China Academy of Building Research
2	China Academy of Urban Planning & Design	China Academy of Building Research	Tongji University	China Academy of Building Research	Tongji University	Tongji University
3	Harbin Institute of Technology	Tongji University	Tsinghua University	Tsinghua University	Tsinghua University	Tsinghua University
4	Tongji University	China Architecture Design & Research Group	Harbin Institute of Technology	China Architecture Design & Research Group	China Academy of Urban Planning & Design	Xi'an University of Architecture and Technology
5	China Architecture Design & Research Group	Beijing Urban Construction Group Co., Ltd	China Architecture Design & Research Group	Beijing Institute of Architectural Design Co., Ltd	China Architecture Design & Research Group	China Institute of Building Standard Design & Research Co., Ltd.

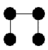
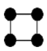
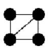
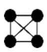
The number of subgroups formed by 3 and 4 nodes in the CIN and the random network was calculated using complete enumeration. The results of NMA are summarized in Table 8.

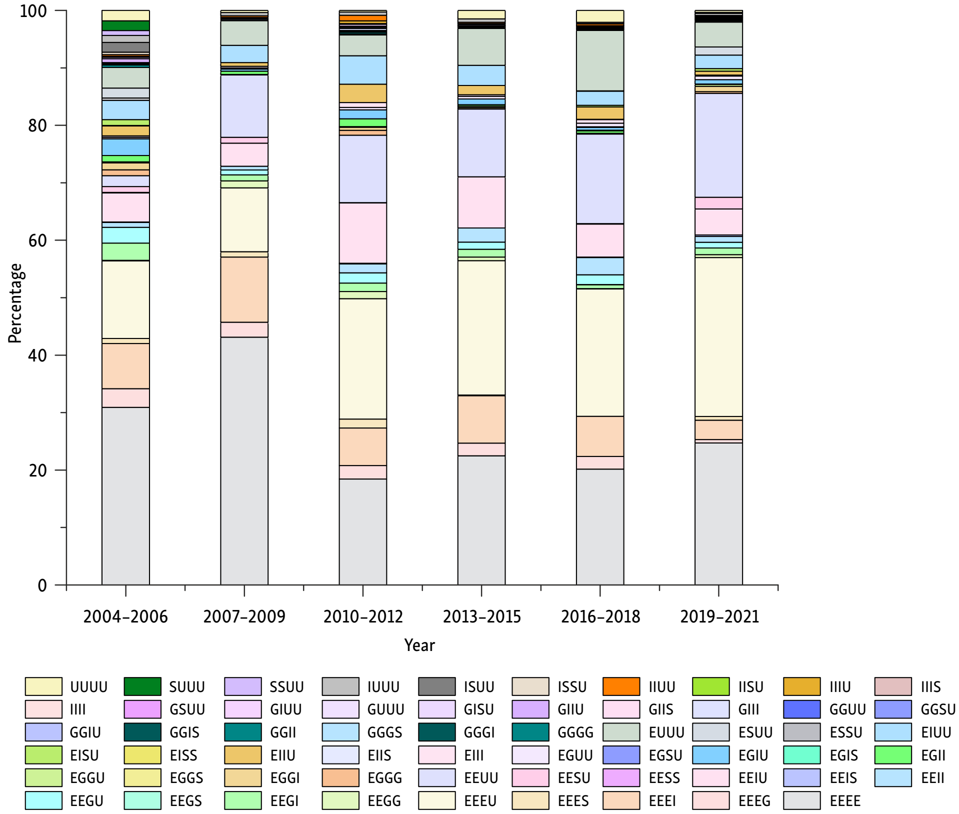
The number of a specific subgroup in a CIN is denoted by Nreal. Creal is the relative number of the subgroup, i.e., the ratio of the actual number of that subgroup in a CIN to the number of all subgroups formed with the same number of nodes. According to Table 8, the collaborative structure formed among innovation organizations in China's construction industry is dominated by subgroups 3-a and 4-a. The p-value is a metric for determining the significance level of the specific motifs discovered. A p-value less than 0.05 means that the identified motif is significant. From Table 8, the Z-Scores of subgroups 3-b, 4-c, 4-e, and 4-f were greater than 0 and their p-values are 0.000, indicating that these subgroups are significantly motifs in the CIN. The Z-Scores of subgroups 3-a, 4-a, 4-b, and 4-d were less than 0 and their p-values are 1.000, indicating that they are antimotifs in the CIN. This conclusion is consistent with the results of Liu et al. (2021b) on the NMA of contractor collaboration networks and Wang et al. (2023b) on the NMA of owner-contractor collaboration networks. It suggests that subgroups 3-b, 4-c, 4-e, and 4-f were the dominant localized patterns in the CIN of China's construction industry. These four subgroup structures all contain , a tripartite collaboration structure with a close connection and stable structure. However, the results differ from Milazzo's et al. (2022) findings on the European air transportation network, which showed that the subgroups 3-a and 4-a are network motif structures in the European air transport network. Subgroups 3-a and 4-a represent the connection pattern of transit hub nodes and help to solve the problem of air flight with limited transportation distance, thus appearing more frequently in the air transportation network. As a collaborative innovation network (CIN) among innovation organizations is constructed in this study, the 3-node or 4-node subgroup structure reflects collaboration among 3 or 4 innovation organizations. Compared with the subgroups with the same number of nodes, the closeness of collaboration among innovation organizations in subgroups 3-a and 4-a is low. So, they have not been the motifs in the CIN of the construction industry. Although subgroups 3-a and 4-a are network anti-motifs, their number in the CIN is significantly larger than that of other subgroups within the same node. Therefore, the abundance of subgroups 3-a and 4-a in CIN is consistent with its scale-free characteristics.

Z-Score can reflect the importance of a motif structure in the network. The larger the Z-Score of a network motif, the more important it is in the network (Pu et al., 2021). Table 5 shows that the Z-Score of subgroup 4-f is higher than that of the other subgroups, which indicates that subgroup 4-f appears more in the CIN. Subgroup 4-f represents the mutual collaboration among the four innovation organizations. Like patent networks and dissertation co-authorship networks, four and more innovation organizations participating in the CSTAC project all can form subgroup 4-f. The percentage of CSTAC-winning projects which involve four or more organizations to all projects increased over time (17.34%, 22.81%, 26.51%, 35.98%, 36.58%, and 44.32%, respectively). Consequently, the presence of subgroups 4-f in the CIN gradually increased. The embedding of subgroups 4-f can effectively improve the tightness of the network.

Subgroup 4-f has different categories depending on the involved innovation organizations of government (G), enterprise (E), university (U), and institute (I). Figure 3 shows the percentage change of different types during the study period. As can be seen from Figure 3 that collaborative patterns such as IUUU and EGII no longer appear in CSTAC in recent years. The innovation collaborative patterns involving four organizations are mainly EEEE, EEEU, and EEUU. From 2004 to 2006, the collaborative pattern of EEEE accounted for the largest proportion, which indicates that enterprises were the main participants of technology innovation collaborations in the construction industry during that period. After that, the proportion of collaborative patterns in which enterprises and universities are involved (such as EEEU and EEUU) has increased. During 2019–2021, the EEEU collaborative pattern had the largest share, followed by the EEUU pattern, and the share of the EEEE pattern decreased. This indicates that collaborative innovation in China's construction industry has been mainly dominated by university-enterprise collaboration in recent years. During the study period, EGIU pattern has always accounted for a relatively low percentage. Li and Zhou (2022) argued that the collaborative pattern of EGIU is an effective four-party collaborative pattern in technology innovation. In this pattern, enterprises can provide the R&D funds and results transformation platform, universities and research institutions have strong R&D capabilities, and the government can provide support for technology innovation. Zhang and Wang (2022) proved that the introduction of research institutions to build an industry-university-research collaborative innovation platform can improve innovation efficiency. However, the innovation organizations in the 4-f subgroup of the CIN in China's construction industry are still dominated by enterprises and universities, and the role of government, research institutions, and industry associations needs to be further strengthened.

Table 8. The results of NMA

ID	Motif Shape	Motif Type	Indicator	2004–2006	2007–2009	2010–2012	2013–2015	2016–2018	2019–2021
3-a		antimotif	N_{real}	6113	6408	14026	21186	26198	65085
			Z-Score	–42.60	–52.65	–81.64	–67.75	–64.54	–43.95
			P-Value	1.000	1.000	1.000	1.000	1.000	1.000
			C_{real} (%)	85.91	85.84	86.33	88.44	89.35	93.66
3-b		motif	N_{real}	1003	1057	2221	2770	3123	4408
			Z-Score	42.60	52.65	81.64	67.75	64.54	43.95
			P-Value	0.000	0.000	0.000	0.000	0.000	0.000
			C_{real} (%)	14.09	14.16	13.67	11.56	10.65	6.34
4-a		antimotif	N_{real}	79227	60603	212314	356658	477372	1718310
			Z-Score	–16.38	–17.60	–24.65	–25.22	–24.25	–16.12
			P-Value	1.000	1.000	1.000	1.000	1.000	1.000
			C_{real} (%)	59.78	51.41	57.51	56.96	57.64	63.23
4-b		antimotif	N_{real}	21012	28396	76096	134865	187697	622305
			Z-Score	–33.29	–31.60	–37.67	–41.04	–41.24	–48.40
			P-Value	1.000	1.000	1.000	1.000	1.000	1.000
			C_{real} (%)	15.85	24.09	20.61	21.54	22.66	22.90
4-c		motif	N_{real}	29620	26628	74595	122735	151371	349951
			Z-Score	14.94	16.29	22.37	23.17	23.54	16.21
			P-Value	0.000	0.000	0.000	0.000	0.000	0.000
			C_{real} (%)	22.35	22.59	20.21	19.60	18.28	12.88
4-d		antimotif	N_{real}	48	64	139	332	446	1758
			Z-Score	–9.87	–9.95	–12.28	–13.42	–14.42	–16.15
			P-Value	1.000	1.000	1.000	1.000	1.000	1.000
			C_{real} (%)	0.04	0.05	0.04	0.05	0.05	0.07
4-e		motif	N_{real}	1462	1122	3470	8184	7765	20916
			Z-Score	5.89	5.95	13.04	18.36	12.72	10.52
			P-Value	0.000	0.000	0.000	0.000	0.000	0.000
			C_{real} (%)	1.10	0.95	0.94	1.31	0.94	0.77
4-f		motif	N_{real}	1168	1069	2577	3388	3583	4287
			Z-Score	114.11	130.12	217.91	126.11	117.84	40.86
			P-Value	0.000	0.000	0.000	0.000	0.000	0.000
			C_{real} (%)	0.88	0.91	0.70	0.54	0.43	0.16



Note: E-Enterprise; U-University; I-Research Institute; G-Government; S-Social Group

Figure 3. Proportion of different types of subgroup 4-f from 2004 to 2021

5. Conclusions

In this study, a CIN of China's construction industry was established based on the dataset of projects that won CSTAC in 2004–2021. The macrostructural characteristics and evolution laws of the CIN were explored using the network-level and node-level indicators in the SNA method, and the microstructure of the CIN and the main collaborative patterns of innovation organizations were investigated using the NMA method.

The main conclusions are as follows. (i) During the study period, the size of the CIN in China's construction industry has increased, but the island effect has led to the deterioration of the network's connectivity. (ii) The CIN of China's construction industry presented the characteristics of scale-free and small-world, with a few organizations holding many technological innovation resources. The evolution of CIN has seen the emergence of many innovation communities of increasing size. (iii) There is a giant component in the CIN. The size and overall cohesion of the giant component has increased over time, but the connections between innovation organizations have become sparse. (iv) China Academy of Building Research (E1469) and Tongji University (U116) played key roles in the technological innovation of China's construction industry. Given its high degree and closeness centrality, China Academy of Building Research (E1469) was a driver for technology innovation. Tongji University (U116), with high betweenness centrality, played the role of intermediary in the technology innovation of the construction industry. (v) In the CIN of China's construction industry, the collaborative pattern of enterprise-enterprise and enterprise-university were the main collaborative patterns during the study period and the latter have become increasingly dominant.

The findings highlight the following policy implications:

(1) The results show that most organizations have low participation in collaborative innovation. Collaborative innovation can shorten the R&D cycle, save transaction costs, and realize complementary advantages. Therefore, it is necessary to further promote collaborative innovation to improve the level of technological innovation in China's construction industry. Policymakers can establish regional innovation clusters for the construction industry, offering financial, land, and policy support to promote the clustering and collaborative innovation of enterprises, universities, and research institutions in the region. The industry authorities should play a guiding and service role in industry-university-research collaborative innovation. Available measures include setting up industry-university-research collaboration projects, designing incentive mechanisms, formulating collaboration guidelines, and promoting international exchanges. Enterprises at the edge of the CIN should enhance their innovation capabilities by increasing R&D investment and recruiting talented R&D personnel. They can also integrate into the giant cluster in the CIN by participating in industry forums and technology exchanges.

(2) According to the results, some organizations with high centrality in CIN (e.g., China Academy of Building Research, Tongji University, etc.) played a key role in the innovation knowledge diffusion or the collaboration among innovation organizations. The following recommendations can be made: Firstly, policymakers can establish special funds to prioritize support for collaborative innovation between organizations with high centrality and other entities, promoting the implementation and transformation of results. Secondly, industry authorities can designate these core organizations as pilot demonstration units for innovation and encourage them to disseminate successful experiences and models by organizing forums and symposiums on collaborative innovation in the construction industry. Finally, core enterprises and universities should take a leading role in research and development in emerging technologies (e.g., blockchain, internet of things, artificial intelligence) to advance the development of new technologies in the construction industry.

(3) The results show that enterprise-enterprise and enterprise-university is the most common collaborative innovation pattern in China's construction industry and more and more universities have been involved in collaborative innovation. Although universities have advantages in knowledge creation and dissemination, they lack results transformation platforms. And although construction enterprises have sufficient R&D funds, they often lack high-level R&D talents. Collaboration between the two can complement each other's advantages and create more new technologies. Some suggestions can be put forward to promote university-enterprise collaboration from four aspects of policymakers, industry authorities, enterprises, and universities as follows. Firstly, it is recommended that policymakers devise policies involving tax incentives and financial subsidies to facilitate collaboration between enterprises and universities, thereby encouraging collaborative innovation. Concurrently, intellectual property protections should be enhanced to ensure that enterprises and universities secure their rightful interests during the innovation process and reduce the risk of infringement. Secondly, industry authorities should encourage enterprises and universities to take the initiative to explore new patterns of collaborative innovation and strengthen the construction of collaborative innovation platforms to promote cooperation between them. Thirdly, construction enterprises can actively invite university researchers to participate in enterprise technology innovation, to enhance enterprise innovation effectiveness and strengthen their core competitiveness. Finally, universities can establish incentive mechanisms to motivate researchers to engage in university-enterprise collaboration. With the support of resources from enterprises, universities may improve the conversion rate and applicability of research results.

This study has three contributions. First, previous studies on CIN mainly focused on high-tech industries and less on traditional industries such as the construction industry. We studied the structural characteristics and evolutionary mechanisms of CIN in China's construction industry, expanding the study field of CIN. Second, previous studies on CIN have only focused on the macrostructure of the network and less on its microstructural characteristics. This study proposed a research framework that combines SNA and NMA, which can reveal both the macrostructural and microstructural characteristics of the network. The study framework can provide a new research idea for the analysis of CIN in the construction industry and other industries. Third, this study explored the evolution of the CIN in China's construction industry from a dynamic perspective. The findings can provide valuable insights for understanding the structural characteristics and evolution laws of the CIN, and the collaborative patterns among technology innovation organizations in China's construction industry, which can provide references for formulating technology innovation strategies in the industry.

This study contributes new insights into theory and practice but still has some limitations. First, the results were obtained based on an analysis of China's construction industry, which can provide insights for the collaborative innovation of construction industry in other countries and other industries. However, different countries and industries have differences in innovation development foundation, development stage, and institutional system, and need to adopt different innovation models and strategies according to local conditions. The structural characteristics of CIN in the construction industry of other countries can be explored and compared in future studies. Second, this study explored the macrostructural characteristics and microstructural characteristics of CIN in China's construction industry and their evolution laws, and revealed the status of collaborative innovation. Future studies can further explore the influence mechanism of network endogenous structural factors, node attribute factors and exogenous covariate factors on the evolution of CIN using the temporal exponential random graph model. Structural equation modeling method can also be used to explore the relationship between CIN and innovation performance.

Acknowledgements

We are thankful to the editor and anonymous referees for their valuable comments and guidance.

Funding

This work was supported by the National Social Science Fund of China under Grant [number: 22BJY232].

Author contributions

FW and MC conceived the study and were responsible for the design and development of the data analysis. FW were responsible for data collection and analysis. FW and MC were responsible for data interpretation. FW wrote the original draft of the article. MC revised the original draft.

Disclosure statement

All authors have not any competing financial, professional, or personal interests from other parties.

References

Alsomiri, M., Liu, Z., Abadel, A. A., & Li, M. (2023). Revision and development of material models of ultra-high performance concrete containing coarse aggregate and applications in structural-level flexural response predictions. *Structures*, *51*, 332–350. https://doi.org/10.1016/j.istruc.2023.03.058

Andersson, D. E., Galaso, P., & Sáiz, P. (2019). Patent collaboration networks in Sweden and Spain during the Second Industrial Revolution. *Industry and Innovation*, *26*(9), 1075–1102. https://doi.org/10.1080/13662716.2019.1577720

Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, *286*, 509–512. https://doi.org/10.1126/science.286.5439.509

Barabási, A. L., & Bonabeau, E. (2003). Scale-free networks. *Scientific American*, *288*(5), 60–69. https://doi.org/10.1038/scientificamerican0503-60

Barabási, A. L., & Oltvai, Z. N. (2004). Network biology: Understanding the cell's functional organization. *Nature Reviews Genetics*, *5*(2), 101–115. https://doi.org/10.1038/nrg1272

Breschi, S., & Lenzi, C. (2016). Co-invention networks and inventive productivity in US cities. *Journal of Urban Economics*, *92*, 66–75. https://doi.org/10.1016/j.jue.2015.12.003

Cheng, M., Yi, X., Wang, F., & Cheng, X. (2023). Measuring the technological innovation efficiency of listed construction companies in China. *Construction Management*, *27*, 5057–5070. https://doi.org/10.1007/s12205-023-2083-8

Clauset, A., Newman, M. E. J., & Moore, C. (2004). Finding community structure in very large networks. *Physical Review E*, *70*(6), Article 066111. https://doi.org/10.1103/PhysRevE.70.066111

Clauset, A., Shalizi, C. R., & Newman, M. E. J. (2009). Power-law distributions in empirical data. *SIAM Review*, *51*(4), 661–703. https://doi.org/10.1137/070710111

De Iudicibus, A., Prota, L., & Savoia, F. (2024). Assessing the role of technological districts in regional innovation policies: A network analysis of collaborative R&D projects. *Journal of Technology Transfer*. https://doi.org/10.1007/s10961-024-10088-4

De Noni, I., Orsi, L., & Belussi, F. (2018). The role of collaborative networks in supporting the innovation performances of lagging-behind European regions. *Research Policy*, *47*(1), 1–13. https://doi.org/10.1016/j.respol.2017.09.006

Dou, B., & Bo, Q. (2022). Characteristics and dynamics of BIM adoption in China: Social network analysis. *Journal of Construction Engineering and Management*, *148*(6), Article 04022025. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002276

Dou, Y., Xue, X., Wang, Y., Xue, W., & Huangfu, W. (2021). Evaluation of enterprise technology innovation capability in prefabricated construction in China. *Construction Innovation*, *22*(4), 1059–1084. https://doi.org/10.1108/ci-12-2020-0196

Galaso, P., & Kovarik, J. (2021). Collaboration networks, geography and innovation: Local and national embeddedness. *Papers in Regional Science*, *100*(2), 349–378. https://doi.org/10.1111/pirs.12578

Graf, H. (2011). Gatekeepers in regional networks of innovators. *Cambridge Journal of Economics*, *35*(1), 173–198. https://doi.org/10.1093/cje/beq001

Hwang, I. (2023). Evolution of the collaborative innovation network in the Korean ICT industry: A patent-based analysis. *Technology Analysis* & *Strategic Management*, *35*(2), 221–236. https://doi.org/10.1080/09537325.2021.1971191

Han, Y., Li, Y., Taylor, J. E., & Zhong, J. (2018). Characteristics and evolution of innovative collaboration networks in architecture, engineering, and construction: Study of national prize-winning projects in China. *Journal of Construction Engineering and Management*, *144*(6), Article 04018038. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001499

Hu, F., Mou, S., Wei, S., Qiu, L., Hu, H., & Zhou, H. (2024a). Research on the evolution of China's photovoltaic technology innovation network from the perspective of patents. *Energy Strategy Reviews*, *51*, Article 101309. https://doi.org/10.1016/j.esr.2024.101309

Hu, F., Qiu, L., Wei, S., Zhou, H., Bathuure, I. A., & Hu, H. (2024b). The spatiotemporal evolution of global innovation networks and the changing position of China: a social network analysis based on cooperative patents. *R&D Management*, *54*(3), 574–589. https://doi.org/10.1111/radm.12662

König, M. D., Battiston, S., Napoletano, M., & Schweitzer, F. (2011). Recombinant knowledge and the evolution of innovation networks. *Journal of Economic Behavior* & *Organization*, *79*(3), 145–164. https://doi.org/10.1016/j.jebo.2011.01.007

Li, T., & Zhou, X. (2022). Research on the mechanism of government-industry-university-institute collaborative innovation in green technology based on game-based cellular automata. *International Journal of Environmental Research and Public Health*, *19*(5), Article 3046. https://doi.org/10.3390/ijerph19053046

Li, F., Liu, W., & Bi, K. (2021). Exploring and visualizing spatial-temporal evolution of patent collaboration networks: A case of China's intelligent manufacturing equipment industry. *Technology in Society*, *64*, Article 101483. https://doi.org/10.1016/j.techsoc.2020.101483

Liu, W., Song, Y., & Bi, K. (2021a). Exploring the patent collaboration network of China's wind energy industry: A study based on patent data from CNIPA. *Renewable* & *Sustainable Energy Reviews*, *144*, Article 110989. https://doi.org/10.1016/j.rser.2021.110989

Liu, L., Zhao, M., Fu, L., & Cao, J. (2021b). Unraveling local relationship patterns in project networks: A network motif approach. *International Journal of Project Management*, *39*(5), 437–448. https://doi.org/10.1016/j.ijproman.2021.02.004

Liu, W., Tao, Y., & Bi, K. (2023). Exploring temporal and spatial evolution of the patent collaboration network: A case study of smart grid field in China. *IEEE Transactions on Engineering Management*, *70*(4), 1605–1620. https://doi.org/10.1109/TEM.2020.2974797

Liu, W., Guo, Y., & Bi, K. (2024). Exploring collaborative innovation evolution of China's energy conservation and environmental protection industry: A social network analysis based on patents. *Journal of Business* & *Industrial Marketing*, *39*(5), 1008–1028. https://doi.org/10.1108/jbim-04-2022-0177

Lu, Y., Liu, B., & Li, Y. (2021). Collaboration networks and bidding competitiveness in megaprojects. *Journal of Management in Engineering*, *37*(6), Article 04021064. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000961

Mao, G., & Zhang, N. (2017). Fast approximation of average shortest path length of directed BA networks. *Physica A*: *Statistical Mechanics and its Applications*, *466*, 243–248. https://doi.org/10.1016/j.physa.2016.09.025

Milazzo, M., Musciotto, F., Micciche, S., & Mantegna, R. N. (2022). Analysis of the structure and dynamics of European flight networks. *Entropy*, *24*(2), Article 248. https://doi.org/10.3390/e24020248

Milo, R., Shen-Orr, S., Itzkovitz, S., Kashtan, N., Chklovskii, D., & Alon, U. (2002). Network motifs: Simple building blocks of complex networks. *Science*, *298*, 824–827. https://doi.org/10.1126/science.298.5594.824

Milo, R., Itzkovitz, S., Kashtan, N., Levitt, R., Shen-Orr, S., Ayzenshtat, I., Sheffer, M., & Alon, U. (2004). Superfamilies of evolved and designed networks. *Science*, *303*, 1538–1542. https://doi.org/10.1126/science.1089167

Neal, Z. (2018). Is the urban world small? The evidence for small world structure in urban networks. *Networks & Spatial Economics*, *18*(3), 615–631. https://doi.org/10.1007/s11067-018-9417-y

Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(23), 8577–8582. https://doi.org/10.1073/pnas.0601602103

Park, S., & Zhong, R. (2022). Pattern recognition of travel mobility in a city destination: Application of network motif analytics. *Journal of Travel Research*, *61*(5), 1201–1216. https://doi.org/10.1177/00472875211024739

Pu, Y., Li, Y., & Wang, Y. (2021). Structure characteristics and influencing factors of cross-border electricity trade: A complex network perspective. *Sustainability*, *13*(11), Article 5797. https://doi.org/10.3390/su13115797

Pu, G., Zhu, X., Dai, J., & Chen, X. (2022). Understand technological innovation investment performance: Evolution of industry-university-research cooperation for technological innovation of lithium-ion storage battery in China. *Journal of Energy Storage*, *46*, Article 103607. https://doi.org/10.1016/j.est.2021.103607

Qiang, G., Cao, D., Wu, G., Zhao, X., & Zuo, J. (2021). Dynamics of collaborative networks for green building projects: Case study of Shanghai. *Journal of Management in Engineering*, *37*(3), Article 05021001. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000892

Roberts, E. B. (2007). Managing invention and innovation. *Research-Technology Management*, *50*(1), 35–54. https://doi.org/10.1080/08956308.2007.11657418

Shen, W., & Xue, J. (2023). Managing project-to-project interfaces for large-scale programmes: A network study in World expo 2020. *International Journal of Project Management*, *41*(2), Article 102438. https://doi.org/10.1016/j.ijproman.2023.102438

Shen, G., Zhu, D., Chen, J., & Kong, X. (2022). Motif discovery based traffic pattern mining in attributed road networks. *Knowledge-Based Systems*, *250*, Article 109035. https://doi.org/10.1016/j.knosys.2022.109035

Steinhaeuser, K., & Chawla, N. V. (2010). Identifying and evaluating community structure in complex networks. *Pattern Recognition Letters*, *31*(5), 413–421. https://doi.org/10.1016/j.patrec.2009.11.001

Stone, L., Simberloff, D., & Artzy-Randrup, Y. (2019). Network motifs and their origins. *Plos Computational Biology*, *15*(4), Article e1006749. https://doi.org/10.1371/journal.pcbi.1006749

Tavella, J., Windsor, F. M., Rother, D. C., Evans, D. M., Guimaraes, P. R. Jr., Palacios, T. P., Lois, M., & Devoto, M. (2022). Using motifs in ecological networks to identify the role of plants in crop margins for multiple agriculture functions. *Agriculture Ecosystems & Environment*, *331*, Article 107912. https://doi.org/10.1016/j.agee.2022.107912

Tomasello, M. V., Napoletano, M., Garas, A., & Schweitzer, F. (2017). The rise and fall of R&D networks. *Industrial and Corporate Change*, *26*(4), 617–646. https://doi.org/10.1093/icc/dtw041

Van Wyk, L., Kajimo-Shakantu, K., & Opawole, A. (2024). Adoption of innovative technologies in the South African construction industry. *International Journal of Building Pathology and Adaptation*, *42*(3), 410–429. https://doi.org/10.1108/ijbpa-06-2021-0090

Wang, X., & Chen, G. (2003). Complex networks: Small-world, scale-free and beyond. *IEEE Circuits and Systems Magazine*, *3*(1), 6–20. https://doi.org/10.1109/MCAS.2003.1228503

Wang, Y., Thangasamy, V. K., Hou, Z., Tiong, R. L. K., & Zhang, L. (2020). Collaborative relationship discovery in BIM project delivery: A social network analysis approach. *Automation in Construction*, *114*, Article 103147. https://doi.org/10.1016/j.autcon.2020.103147

Wang, Z., Wang, K., Wang, Y., & Wen, Z. (2022). A data management model for intelligent water project construction based on blockchain. *Wireless Communications & Mobile Computing*, *2022*, Article 8482415. https://doi.org/10.1155/2022/8482415

Wang, W., Jian, L., Lei, Y., Liu, J., & Wang, W. (2023a). Measurement and prediction of the relationships among the patent cooperation network, knowledge network and transfer network of the energy storage industry in China. *Journal of Energy Storage*, *67*, Article 107467. https://doi.org/10.1016/j.est.2023.107467

Wang, F., Cheng, M., & Cheng, X. (2023b). Exploring the project-based collaborative networks between owners and contractors in the construction industry: Empirical study in China. *Buildings*, *13*(3), Article 732. https://doi.org/10.3390/buildings13030732

Wang, B., Chen, H., Ao, Y., & Liao, F. (2023c). Spatiotemporal differentiation and influencing factors of green technology innovation efficiency in the construction industry: A case study of Chengdu-Chongqing urban agglomeration. *Buildings*, *13*(1), Article 73. https://doi.org/10.3390/buildings13010073

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature*, *393*, 440–442. https://doi.org/10.1038/30918

Yu, L. (2023). Project engineering management evaluation based on GABP neural network and artificial intelligence. *Soft Computing*, *27*(10), 6877–6889. https://doi.org/10.1007/s00500-023-08133-9

Yu, X., Cui, Y., Chen, Y., Chang, I., & Wu, J. (2022). The drivers of collaborative innovation of the comprehensive utilization technologies of coal fly ash in China: A network analysis. *Environmental Science and Pollution Research*, *29*(37), 56291–56308. https://doi.org/10.1007/s11356-022-19816-5

Yu, P., Cai, Z., Jiang, F., & Sun, Y. (2023). Evaluation and analysis of leading position in hydrogen fuel cell vehicle innovation network and the influential factors: a case of patent citations in China. *Environmental Science and Pollution Research*, *30*(18), 53339–53354. https://doi.org/10.1007/s11356-023-25969-8

Zhang, S., & Wang, X. (2022). Does innovative city construction improve the industry-university-research knowledge flow in urban China?. *Technological Forecasting and Social Change*, *174*, Article 121200. https://doi.org/10.1016/j.techfore.2021.121200

Zhao, S., & Li, J. (2022). Impact of innovation network on regional innovation performance: Do network density, network openness and network strength have any influence?. *Journal of Science and Technology Policy Management*, *14*(5), 982–999. https://doi.org/10.1108/JSTPM-05-2022-0084

Zhao, X., & Cheah, C. C. (2023). BIM-based indoor mobile robot initialization for construction automation using object detection. *Automation in Construction*, *146*, Article 104647. https://doi.org/10.1016/j.autcon.2022.104647