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Unraveling the dynamics and identifying the "superstars" of R&D alliances in IUR collaboration: a two-mode network analysis in China

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The collaborations between industry, university, and research institutes have become more relevant with the trend of knowledge commercialization, while whether there exists a "superstar" in R&D alliance networks, who played a key role in the diffusion and transfer of technology and knowledge, remains unexplored. Based on R&D activities information of joint patents in China, this study applied two-mode network analysis to understand the R&D alliance network of the industry-university-research institute (IUR) collaboration. Three types of networks, collaboration networks, knowledge networks, and inter-organizational technology networks among IUR are developed, and their evolution process is analyzed at different levels, including overall structure, individual characteristics, and temporal evolution among IUR. The results show that no permanent superstar is being the dominant position. Distinct modes have been emerging in different periods: in the formation period, the mode is U-R, I-U, U, R, I; in the growth period, the mode is I-R, I-U, I-U-R; in the mature period, the mode is I-U-R. In addition, different technology classes were aggregated in different periods. This paper attempts to provide countermeasures and recommendations for enterprises, universities, and research institutions to enable the success of their collaborations.

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Introduction

The positive spillover effect of research and development (R&D) activities between firms has been widely recognized as beneficial for enhancing each company's innovation capability. Numerous studies have demonstrated this effect (Hanaki et al. 2010; Kang and Park 2012; Feldman and Kelley 2006). This effect tends to be more pronounced among companies operating within the same knowledge and technology domain (Jaffe 1986; Iammarino and McCann 2006; Laursen and Salter 2006; O'Mahony and Vecchi 2009; Atasoy et al. 2018), particularly those that invest sufficiently in R&D to maintain their absorptive capacity for external knowledge (Ahuja 2000; Cohen and Levinthal 1989; Laursen and Salter 2006; Schot and Steinmueller 2018; Papanastassiou et al. 2020; Arora et al. 2018). As companies enter into strategic alliances or establish partnerships with research-oriented universities and public research institutes, the positive spillover effect will be further reinforced (Lyu et al. 2019; Yang et al. 2022). Thus, industry-university-research institute collaboration has bloomed around the globe.

It is evident that a wide range of collaboration modes have emerged. In the United States, the Industry-University Cooperative Research Center model (I/UCRC model), the Science and Technology Park model[1], the technology business incubator, the patent licensing and technology transfer model, and the high technology business development model have occurred. The German model refers to enterprise-focused R&D project cooperation, consortium-type cooperation, and technology transfer center. The Japanese model of commissioned research, joint research, science city, and high-tech park, the Korean Daedeok Research Park, and the British Cambridge Science Park are representatives of high-tech industrial parks, where the leading and following organizations are embedded in the high-tech innovation network along with the flow of knowledge to acquire competitive advantages. However, it is worth noting that most studies on collaboration modes have primarily focused on the developed world.

China, as one of the developing countries, also witnessed the rapid growth of R&D alliance network organizations in industrial parks in recent years (Hershberg et al. 2007; Kafouros et al. 2015; Qiu et al. 2017). In China's industrial parks, the innovation organizations are highly interconnected and closely linked, promoting the whole innovation capacity. For example, well-known enterprises such as Lenovo and Baidu in Zhongguancun Science and Technology Park are embedded in the communication and electronics technology R&D alliance network of Zhongguancun Science and Technology Park, integrating the knowledge system of industry, university, and research institute by multiple cooperation of more than 200 innovative organizations.

The objective of this paper is to investigate the formation and evolution of the R&D alliance network in the context of China's IUR collaboration. We aim to identify the key players in the R&D alliance network, which serves as a crucial mechanism for the dissemination and exchange of technology and knowledge during specific time periods. To achieve this, we will construct three networks: collaboration networks, knowledge networks, and inter-organizational technology networks among IUR. Through the application of two-mode analysis, we will examine the overall structure, individual characteristics, and temporal changes within these three networks.

Literature Review

Network analysis has been widely used in studies concerning partners and their relationships in collaboration. One stream built up a collaboration network by using co-author relationships for academic papers (Hou et al. 2008; Pepe 2011; Yang et al. 2021; Liang and Liu 2018; Gilding et al. 2020), while another stream concentrates on the knowledge exchange and technology collaboration between specific organizations, regions, and countries in joint patent application data (Choe and Lee 2017; Guan and Liu 2016; Wang et al. 2014; Paruchuri and Awate 2017). Our paper contributes to the latter one, termed patent network analysis.

Although previous studies in patent network analysis have explored a variety of diverse structures and properties of the patent collaboration network, there is no clear and unified definition of the network formats. One major reason might be that the R&D alliance networks are complex by nature, constituted by the multi-level links connecting participants by technologies and knowledge that R&D organizations have created (Dyer and Hatch 2006; Mina et al. 2014). There are three main types of network structures. The first is the collaboration network, which emphasizes the cooperation relationship between alliance organizations by holding innovation activities in pursuit of the benefits of all participants (Wang et al. 2014; Guan and Liu 2016; Gild-ing et al. 2020). The second is the knowledge network, which carries the knowledge elements of innovation organizations' knowledge accompanied by the flow of knowledge elements (Wang et al. 2014; Reagans and McEvily 2003; Iammarino and McCann 2006; Tortoriello et al. 2012; Paruchuri and Awate 2017). The last one is an inter-organizational technology network, which closely links the nodes of the two different modalities embedded in the innovation organization. The technology modalities interact and penetrate each other, enabling multiple strengths, inverse multiple participation rates, and co-occurrence relationships. Thus, when embedded in the network, innovation organizations can establish collaborative connections between one another to accomplish projects. Additionally, they can establish technological connections to acquire heterogeneous knowledge from other nodes in the network, facilitating the innovation and recombination of knowledge, ultimately achieving high-quality integration among innovation organizations. (Berardo 2014; Boccaletti et al. 2014).

The concept of a two-mode network recognizes that organizations can simultaneously participate in multiple networks with different characteristics (Connolly 2005; Laumann et al. 1978; Zhang et al. 2019). Organizations often take on multiple roles and engage in various activities to establish connections with different types of social contacts. As a result, they form parallel networks that serve different functions and involve different sets of contacts. This approach provides a deeper understanding of R&D alliance networks. In a similar vein, Chang (2017) applied a two-mode network analysis to highlight focal technology fields, technology development trends, and the distribution of technology networks in university-industry collaboration (UIC). However, his work focused on the UIC network at the country level, showcasing the creative efforts and pivotal role of different countries in promoting emerging technology. In contrast, our research takes a micro-level perspective, examining the organizational level. Since existing research does not integrate the inter-organizational network with the technology network, nor does it consider the structure, relationships, and integration of the inter-organizational technology network, our research will delicately fill the gap.

Research design and data

Our research focuses on Chinese strategic emerging industries, specifically energy-saving and environmental protection industries, new energy vehicle industries, high-end equipment manufacturing industries, new energy industries, new materials industries, new generation information technology industries, and bio-industries. We selected these industries for several reasons. Firstly, they are considered strategic emerging industries in China, which has led to an increase in R&D alliance activities within these sectors. Secondly, these industries undergo significant technological advancements and face intense competition, resulting in frequent patenting of inventions (Phelps 2010; Wang et al. 2014; Guan and Liu 2016). This characteristic allows for the quantification of organizational innovation activities.

We collected data from the China State Intellectual Property Office (SIPO) database, which is widely recognized for its extensive collection of global patents from over 100 countries and 40 patent authorities, including USPTO, EPO, and JPO, among others. This database was chosen due to its comprehensive coverage, allowing us to obtain a precise reflection of China's technology landscape within the strategic emerging industries. To identify patents related to Chinese strategic emerging industries, we employed a keyword-based search strategy similar to the approaches used by Menendez-Manjon et al. (2011), Guan and Liu (2015), and Guan and Liu (2016). This strategy involved a two-step process: initial identification followed by a Boolean "AND" operation to refine the search results. To ensure the exclusion of irrelevant patents, we carefully reviewed the front page of each patent. Through this meticulous filtering process, we obtained a total of 26,704 patents granted between 1995 and 2018.

We used International Patent Classification codes (IPC), as defined by the World Intellectual Property Organization (WIPO), or technological classes defined by the US Patent and Trademark Office (USPTO), as proxies for knowledge components or elements (Carnabuci and Bruggeman 2009; Carnabuci and Operti 2013; Dibiaggio et al. 2014; Guan and Liu 2015; vom Stein et al. 2015). Because of data availability, we used IPC codes in our study. In accordance with common practice, we used the four-digit IPC codes to denote knowledge elements (Guan and Liu 2015; Park and Yoon 2014). The patents we analyzed may have multiple assignees and may be associated with multiple four-digit IPC codes. The data enabled us to construct knowledge networks and inter-organizational technology networks within the Chinese strategic emerging industry. To build the knowledge networks, we utilized joint patent assignees and their shared application of four-digit IPC codes. For the inter-organizational technology networks, we established connections between organizations and patents based on their participation in the development of the patents. We employed a five-year rolling window for this analysis, aided by the Science of Science (Sci2) Tool software. We illustrate the constitutions of the collaboration, knowledge and inter-organizational technology networks in Fig.1.

The analytical framework of this study is depicted in Fig. 2. Firstly, we utilized a web crawler to filter data from the China State Intellectual Property Office (SIPO) patent data filtering information service platform. The filtering process involved selecting patents based on the research institute or research centers, university or college, and enterprise or company that established cross combinations of search types. Secondly, the selected patents were subject to conditional restrictions, as outlined in Fig. 3. Specifically, they had to be authorized invention patents granted between 1995 and 2018. The text data used for constructing the network had to meet certain criteria. Firstly, the patent applicants had to include enterprises, universities, and research institutions. Secondly, there had to be more than two patent technology categories represented in the data. Additionally, the data had to pertain to either enterprises, universities, or research institutes, with only two categories not conforming to the study's standards being excluded. As a result, a total of 26,704 patents granted between 1995 and 2018 were obtained. Among these, 11,763 qualified patents were selected, representing a retention ratio of 44.05% among all crawled data. Furthermore, the analysis involved 849 innovation subjects, as illustrated in Fig. 4.

Analysis results

The definition of several concepts

The index computation of the whole network. This paper uses 6 indexes, including network scale, network density, central potential, average distance, cohesion index and clustering coefficient, to analyze the characteristics of the whole network structure.

Network scale and network density: Network scale refers to the size of a network, which can be measured by the number of nodes or edges in the network. The larger the network scale is, the more opportunities for communication and innovation between nodes there will be. When the network develops to a certain stage, too large a network scale may easily lead to free riding and other opportunistic behaviors, which is not conducive to the improvement of network innovation efficiency (Markov et al. 2013). Network density is a crucial measure that determines the level of connectivity among nodes within a network. It can be quantified by dividing the total number of edges in the network by the maximum number of potential edges. The higher the network density and the stronger the connections between members, the more efficiently innovative knowledge and achievements can be disseminated. A network with high density significantly reduces the average path length for information transmission and accelerates the flow of information (Chen et al. 2020).

Central potential: Central potential is a measure of the importance of a node in a network. It can be calculated using various centrality measures such as degree centrality, betweenness centrality, and eigenvector centrality (Stojčić 2021). Central potential reflects the extent to which the network is constructed around one or several points, that is, the extent to which the relationships in the network are concentrated on one or several central nodes. A higher degree of central potential indicates a more centralized network structure. The smaller the closeness of central potential, the shorter the distance between the node and other nodes is, which means that the network is more likely to be controlled by a few nodes and the centrality of the node is higher. The larger the betweenness central potential becomes, the higher the probability of the network being controlled by a few nodes will be (Sprong et al. 2021).

Average distance, cohesion index and clustering coefficient: Average distance is the average shortest path length between all pairs of nodes in a network. It can be calculated using algorithms such as Dijkstra's algorithm or Floyd-Warshall algorithm (Palit et al. 2022). Cohesion index is a measure of how tightly connected a group of nodes are in a network. It can be calculated using various measures such as modularity, community detection algorithms, or clustering algorithms (Vo et al. 2020). The larger the cohesion index based on distance, the more cohesive the whole network is. The distance and cohesion index can reflect the network efficiency of the whole network. The smaller the distance and the higher the cohesion index, the closer the relationship between network members is. Clustering coefficient is a measure of how likely nodes in a network are to form clusters or groups (Yuan et al. 2021). It can be calculated by dividing the number of triangles in a network by the number of possible triangles. The greater the clustering coefficient, the stronger the clustering degree of the network becomes. This indicates that the connections between nodes are closer, resulting in a more efficient network structure (So et al. 2021).

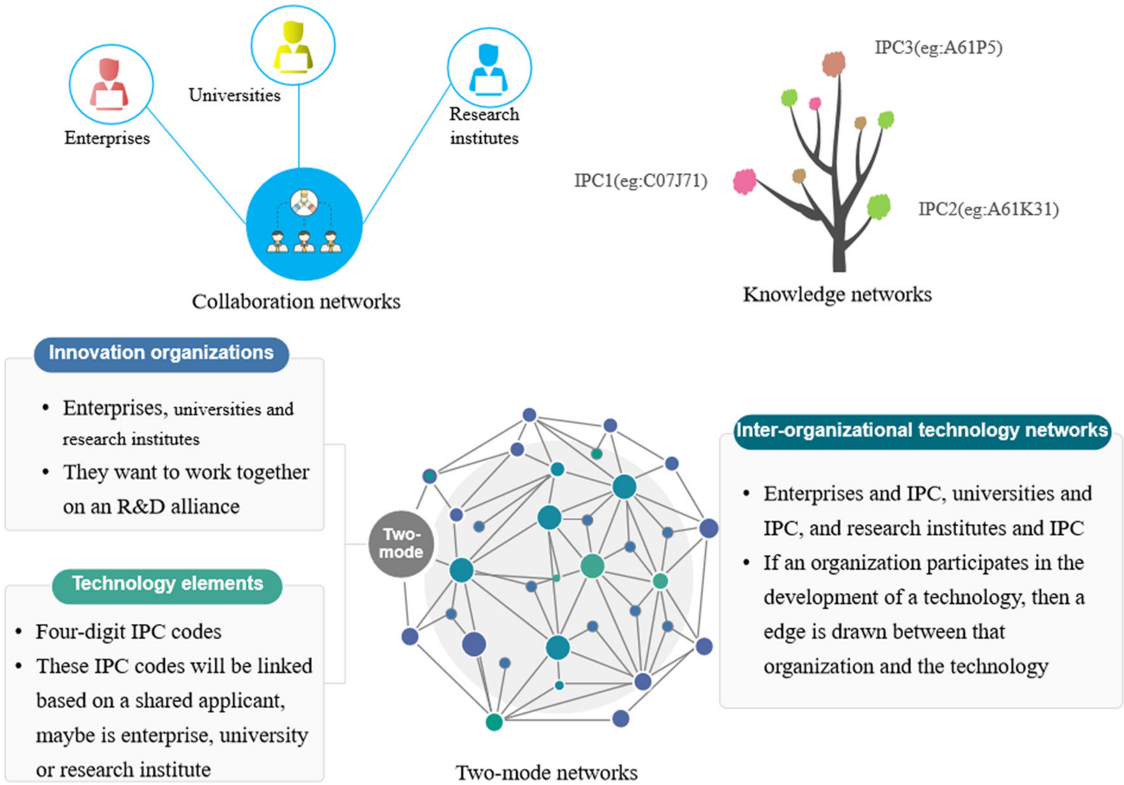

Fig. 1 Constitutions of the collaboration, knowledge and inter-organizational technology networks.

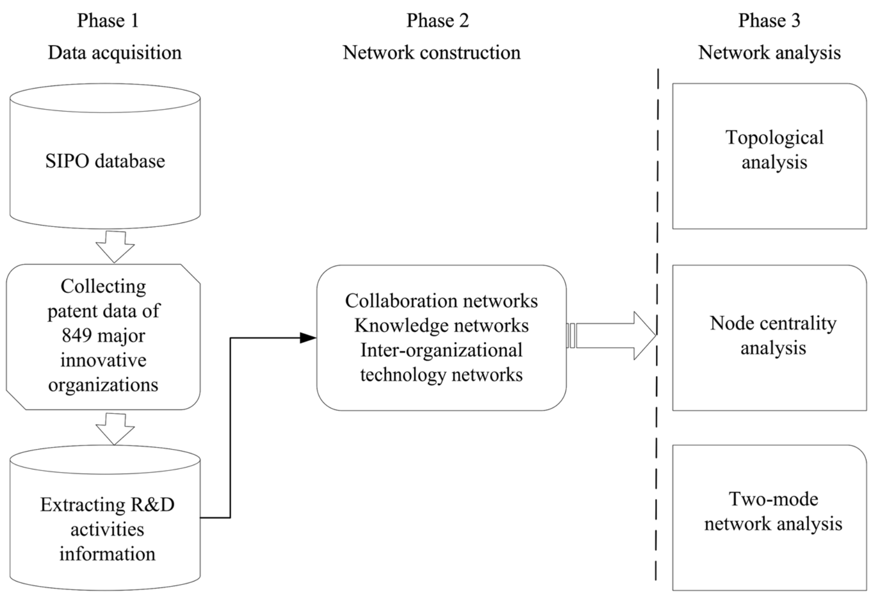

Fig. 2 Research flow chart.

The indexes computation of the ego network. This paper uses 3 indexes: degree of centrality, betweenness centrality, and structural hole to analyze the status of individual nodes in the network.

Degree centrality: Degree centrality reflects the node's ability to communicate. The larger the degree of centrality, the more frequent the communication activities will be (Shijaku and Ritala 2023). The node will have more opportunities to contact various types of information. It occupies a pivotal position in the network, making it more convenient to learn from other nodes. If a node has the highest degree of centrality, it is considered to be located at the center of the network(Shijaku and Ritala 2023; Kumar and Zaheer 2019). The node is easier to obtain innovation resources to innovate, rather than imitate the surrounding nodes, and its innovation performance may be higher.

Betweenness centrality: Betweenness centrality reflects the extent to which a node controls network resources, and a node can appear on the shortest path of any two nodes in the network (Zhao et al. 2023). The betweenness centrality of a node is determined by the number of shortest paths it lies on between pairs of nodes in a network. This centrality measure quantifies the

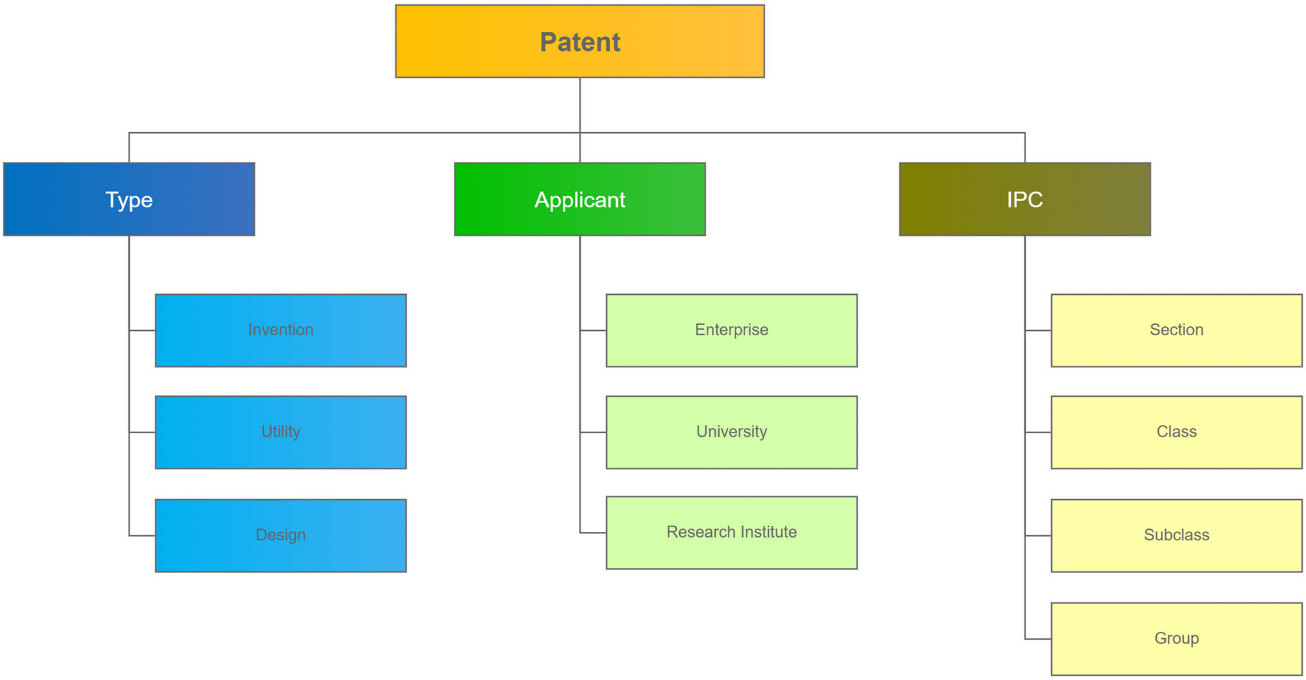

Fig. 3 The distribution of patent.

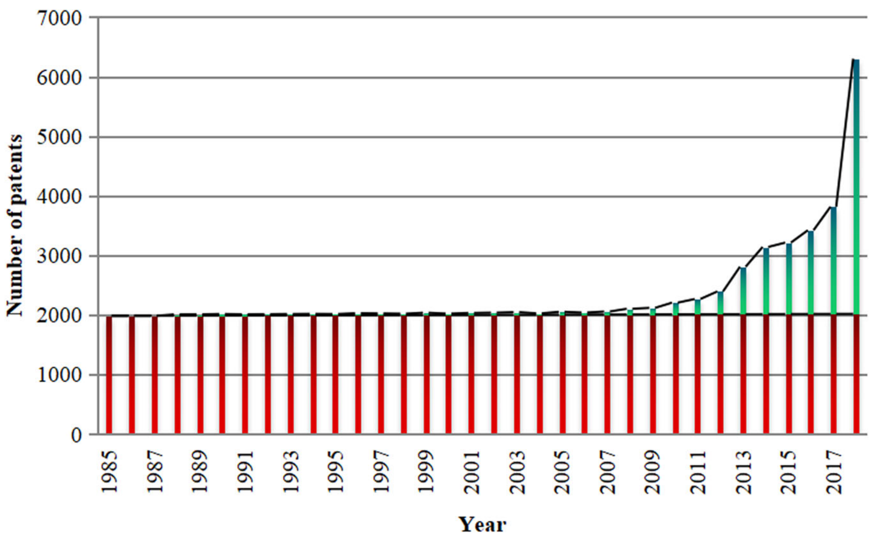

Fig. 4 Patent selection process.

extent to which a node serves as a bridge on the shortest paths between other nodes in the network. Therefore, a node that is on many such paths will have a high betweenness centrality, indicating its importance in facilitating communication and information flow between different parts of the network (Qianqian and Yijun 2020). But this node with relatively low betweenness centrality may play an important intermediary role, so it is in the center of the network. The greater the betweenness centrality, the higher the control over information is. It plays the role of middleman, agent, and broker in the network, and has more control over other nodes (Moldavanova and Akbulut-Gok 2022). It has an information advantage and resource control ability.

Structural hole: The structural hole reflects the non-redundant connections in the network, which is a measure of the network associations between partners. Some individuals connect the densely connected areas for their own purposes and eventually form a strong competitive advantage by changing the network structure (Kumar and Zaheer 2019; Xia and Li 2023). Nodes with rich structure holes have special advantages in resource acquisition and information control, so the resource advantage of a loose network is greater than that of a tight network. Structural hole indicators mainly include effective scale, efficiency, limit degree, and grade degree, among which the limit degree is the most important (Guo et al. 2021; Wen et al. 2021; Flipo et al. 2023).

Analysis of the whole network of IUR collaboration networks. We have considered the five-year planning from the Chinese government's policy and separated data into overlapping time windows. The data cleaned out in Fig. 2 are divided into 19-time windows, which are 1995–1999, 1996–2000, 1997–2001, 1998–2002, 1999–2003, 2000–2004, 2001–2005, 2002–2006, 2003–2007, 2004–2008, 2005–2009, 2006–2010, 2007–2011, 2008–2012, 2009–2013, 2010–2014, 2011–2015, 2012–2016, 2013–2017. Visual analysis and measurement of relevant indexes are carried out on the data of these 19-time windows. Space is limited, and there are similarities in the network topological structure of some periods. Therefore, in the following analysis, we choose the data from some periods for visualization.

In our research, we explore various types of networks, including collaboration networks, knowledge networks, and inter-organizational technology networks. A collaboration network comprises organizations and their collaborative relationships. As the nodes within collaboration networks, organizations connected through social partnerships have the ability to control the diffusion of knowledge and influence subsequent innovative outcomes. Moreover, the connections among these organizations can function as a pathway for acquiring tacit knowledge through social partners.

Knowledge elements serve as the fundamental building blocks of knowledge networks. They encompass a range of facts, concepts, methods, insights, or procedures related to a specific subject. Within our research, explicit technological knowledge elements play a pivotal role as the key components in knowledge networks. In line with previous research (Fleming and Sorenson 2001), the connections that link knowledge elements within knowledge networks are represented by historical patterns of knowledge combinations and the co-application of knowledge elements in patents, specifically, joint patent assignees sharing the application of four-digit IPC codes.

The inter-organizational technology network is often utilized to illustrate the connections between individuals and the parties or events with which they are associated (Snijders et al. 2010). Hence, the inter-organizational technology network is also referred to as affiliation networks (Wasserman and Faust 1994). we expand the concept of affiliation from a broad perspective to encompass both explicit and tacit knowledge elements within organizations.

Evolution of collaboration network topological structure. Collaboration networks based on the IUR collaboration relationship are extracted, and collaboration networks of some time periods are extracted, as shown in Fig. 5, where the size of the node in the figure represents the size of the degree centrality of the node.

As can be seen from Fig. 5, the network centers are relatively prominent and show obvious clustering characteristics. The innovation organizations in the center build more cooperative relationships and have a high centrality. This kind of innovation organization is located at the core of the network and can be called the core subject. At the edge of the cluster or network are the innovation organizations which are not very active in the construction of IUR, showing a low centrality and can be called edge organizations. This change has a relatively high degree of distinction in 2010–2014 and 2011–2015. We can see that the networks in Fig. 5a, b are relatively sparse, the network center is not very prominent, and the connections in the network are relatively few. Many innovative organizations are only connected once or twice. However, the networks in Fig. 5c–e are relatively concentrated. Some innovative organizations show a high centrality and have direct connections with multiple organizations.

From 1995 to 2017, the changes in the number of edges, density, clustering coefficient, average shortest path, and network centralization index of the collaboration network of innovation organizations are shown in Table 1 From 1995 to 2003, the number of edges of the collaboration network increases gradually. The average node degree decreases first and then increases. The overall network density decreases from 0.117 to 0.081, then increases to 0.098, and finally reaches 0.076 from 1999 to 2003. The network clustering coefficient increases first and then decreases, from 0.898 to 0.94 to 0.934. The average shortest path changes from 2.347 in 1995–1999 to 2.687 in 1999- 2003. The network centralization index also experiences a process of first decreasing and then increasing. From 2000 to 2009, the number of edges changed more complicatedly. The number of edges increased the most in 2003–2007 and 2005–2009. The average node degree and the overall network density change relatively regularly and decrease gradually. The clustering coefficient goes through a process of first decreasing, then increasing, and finally decreasing. The average shortest path also experiences a process of first decreasing and then increasing and finally reaching 2.023. The network centralization index decreases year by year, but there are rebounds in 2004–2008 and 2005–2009, which are 0.031 and 0.062 respectively. After the period of 2006–2010, the number of edges and the average node degree show a trend of rapid growth year by year, which indicates that more and more IUR innovation organizations participate in collaboration, and the connections are closer and closer. The density and clustering coefficient of the collaboration networks show a downward trend year by year. The average shortest path goes through a process of first increasing and then decreasing. The network centralization index experiences a process of first increasing, then decreasing and finally increasing.

The initial stage of the network exhibited a low level of connectivity, characterized by a few isolated nodes and small clusters. As the network expanded, the number of nodes and edges increased, resulting in a more interconnected and densely populated network. This is evident in the rise of the average degree and clustering coefficient of the network. Additionally, we observed the emergence of central nodes or hubs, which played a pivotal role in linking various parts of the network. These hubs had a high degree of centrality, indicating their importance in the network. We noted that the emergence of these hubs was a result of the collaboration patterns of researchers, where some researchers were more active in collaborating with others, leading to the formation of clusters around them. The changes in the network structure also reflected the evolution of research topics and themes over time. We have observed that the network underwent a phase of fragmentation, where different clusters emerged around specific research topics. Nevertheless, as time progressed, these clusters amalgamated, leading to a more unified network structure. This integration is evident in the reduction of the network's modularity, signifying enhanced cohesion and reduced fragmentation. In summary, the numerical changes in the evolution of the IUR collaboration network's topological structure exemplify its growth, development, and integration over time. The network became more interconnected, dense, and cohesive, with the emergence of central nodes or hubs playing a crucial role in connecting different segments of the network.

Specifically, according to statistics presented in Fig. 5a, the organizations that displayed relatively high degree of centrality during the period of 2007–2011 encompass Siemens (China) Co., Ltd., Central South University of Forestry and Technology, Hunan University, Nanjing University of Aeronautics and Astronautics, China Electric Power Research Institute, Shandong University, Xi'an Jiaotong University, China Agricultural University, North China Electric Power University, Electric Power Research Institute of Hubei Electric Power Company, Shanghai Jiao Tong University, Beijing University of Science and Technology, State Grid Corporation of China, Donghua University, Shanghai Institute of Special Equipment Inspection and Technical, East China University of Science and Technology, Tsinghua University, South China University of

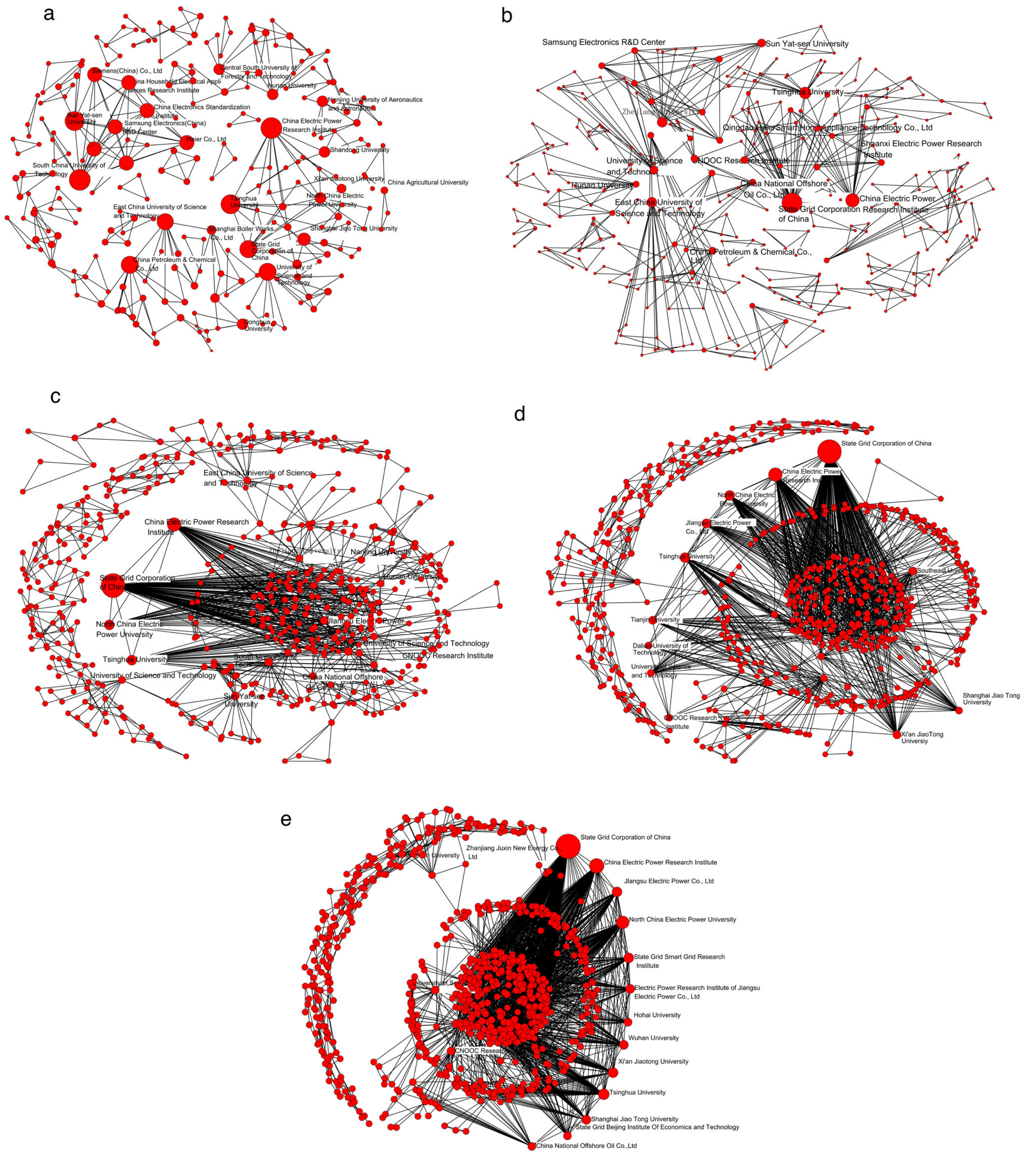

Fig. 5 The evolution of network topology of collaboration network. a Network topology of collaboration network from 2007 to 2011. **b** Network topology of collaboration network from 2008 to 2012. **c** Network topology of collaboration network from 2009 to 2013. **d** Network topology of collaboration network from 2010 to 2014. **e** Network topology of collaboration network from 2011 to 2015.

Technology, Haier Co., Ltd., China Electronics Standardization Institute, Sun Yat-sen University, and Samsung Electronics (China) R&D center. These organizations include universities, enterprises, and research institutes, all of which hold influential positions within the network and establish connections with numerous UIR innovation organizations. They serve as vital nodes in the network and undertake critical innovation projects.

Figure 5b reflects that the organizations with relatively high degree centrality from 2008–2012 include Donghua University, East China University of Science and Technology, Zhejiang University, Sinopec Co., Ltd., Dalian University of Technology, China National Offshore Oil Co., Ltd., CNOOC Research Institute, Central South University of Forestry and Technology, Hunan University, Beijing University of Science and Technology, Nanjing University of Aeronautics and Astronautics, Beijing

Table 1 Main topological indicators of collaboration network from 1995 to 2017.

The year	The number of edges	The average node degree	The standard deviation of node degree	The overall network density	Clustering coefficient	The average shortest path	The network centralization index
1995–1999	102	5.323	14.715	0.117	0.898	2.347	0.143
1996–2000	146	1.022	3.691	0.081	0.924	2.021	0.021
1997–2001	138	0.634	2.878	0.093	0.940	2.112	0.023
1998–2002	138	1.100	5.656	0.098	0.936	2.190	0.048
1999–2003	210	4.596	22.024	0.076	0.934	2.687	0.088
2000–2004	178	5.760	25.664	0.079	0.941	2.256	0.123
2001–2005	150	3.111	13.860	0.079	0.935	1.903	0.092
2002–2006	176	1.180	5.388	0.051	0.945	1.558	0.020
2003–2007	206	0.947	4.850	0.039	0.955	1.523	0.013
2004–2008	170	0.417	1.451	0.037	0.95	1.845	0.031
2005–2009	326	1.138	4.632	0.030	0.942	2.023	0.062
2006–2010	484	4.994	21.489	0.020	0.910	3.028	0.011
2007–2011	730	21.199	93.061	0.013	0.907	3.410	0.025
2008–2012	1014	145.564	680.350	0.011	0.890	3.956	0.127
2009–2013	1872	299.037	1987.727	0.010	0.854	3.452	0.327
2010–2014	2852	377.307	2985.964	0.009	0.846	3.249	0.344
2011–2015	3683	444.208	3603.202	0.009	0.845	3.225	0.326
2012–2016	4672	571.458	5028.135	0.008	0.843	3.124	0.379
2013–2017	5733	632.445	6025.223	0.007	0.841	3.003	0.315

University of Civil Engineering and Architecture, Shanghai Jiao Tong University, Huazhong University of Science and Technology, Shaanxi Electric Power Research Institute, Xi'an Jiaotong University, North China Electric Power University, Shandong University, State Grid Corporation of China, China Electric Power Research Institute, Tsinghua University, South China University of Technology, Samsung Electronics (China) R&D Center, Haier Co., Ltd., China Electronics Standardization Institute, Siemens (China) Co., Ltd., China Household Electric Appliance Research Institute, Qingdao Haier Smart Home Appliance Technology Co., Ltd., and Sun Yat-sen University. Compared to the previous five years, the additions of Sinopec Co., Ltd., Dalian University of Technology, China National Offshore Oil Co., Ltd., and CNOOC Research Institute result in a more compact network topology, closer connections between networks, and more frequent interaction among organizations.

Analysis of Fig. 5c reveals that the organizations with relatively high degree centrality from 2009–2013 mainly consist of East China University of Science and Technology, China Electric Power Research Institute, State Grid Corporation of China, North China Electric Power University, Tsinghua University, Beijing University of Science and Technology, South China University of Technology, China National Offshore Oil Co., Ltd., CNOOC Research Institute, Huazhong University of Science and Technology, Jiangsu Electric Power Company, Hunan University, Nanjing University, and Zhejiang University. Compared to 2008–2012, the additions of China National Offshore Oil Co., Ltd., Nanjing University, and Jiangsu Electric Power Company indicate increased agglomeration within the network. However, it is not as prominent as the multi-group connections observed in the previous period. Notably, this period is predominantly influenced by several key innovation organizations such as State Grid Corporation of China and China Electric Power Research Institute, accounting for over half of the network connections. These organizations gain significant resource advantages and radiate effects to other network organizations during this period.

Examining Fig. 5d, the organizations with relatively high degree centrality from 2010–2014 include the State Grid Corporation of China, China Electric Power Research Institute, North China Electric Power University, Jiangsu Electric Power Company, Tsinghua University, Tianjin University, Dalian University of Technology, Beijing University of Science and Technology, CNOOC Research Institute, Xi'an Jiaotong University, Shanghai Jiao Tong University, and Southeast University. Compared to 2009–2013, Tianjin University, Dalian University of Technology, Xi'an Jiaotong University, Shanghai Jiao Tong University, and Southeast University have been added, all of which are universities, indicating heightened activity among universities during this period. Since the introduction of the concept of strategic emerging industries in 2009, the government has actively promoted their development. Emphasis has been placed on integrating industry, universities, and research institutions, particularly facilitating the timely transformation of university research achievements. As a result, the significance of universities within the network has progressively grown.

According to the findings presented in Fig. 5e, it is evident that from 2011 to 2015, several prominent institutions demonstrated a higher degree centrality in terms of innovation. These institutions include Sun Yat-sen University, Zhanjiang Juxin New Energy Co., Ltd., State Grid Corporation of China, China Electric Power Research Institute, Jiangsu Electric Power Company, North China Electric Power University, State Grid Smart Grid Research Institute, Electric Power Research Institute of Jiangsu Electric Power Co., Ltd., Hohai University, Wuhan University, Xi'an Jiaotong University, Tsinghua University, Shanghai Jiao Tong University, State Grid Beijing Institute of Economics and Technology, and China National Offshore Oil Co., Ltd. In comparison to the previous five years, the newly added institutions are Zhanjiang Juxin New Energy Co., Ltd., North China Electric Power University, State Grid Smart Grid Research Institute, Electric Power Research Institute of Jiangsu Electric Power Co., Ltd., Hohai University, Wuhan University, State Grid Beijing Institute of Economics and Technology, and China National Offshore Oil Co., Ltd. The "2011 plan" introduced in 2011 has played a pivotal role in facilitating UIR collaboration. Over the years, China has established a total of 167 "2011 collaborative innovation centers" led by universities and comprised of research institutes and enterprises. These centers effectively leverage their respective resource advantages. Ultimately, only 14 centers have emerged as the initial group of national collaborative innovation centers under the "2011 plan". This series of initiatives has provided policy support for UIR

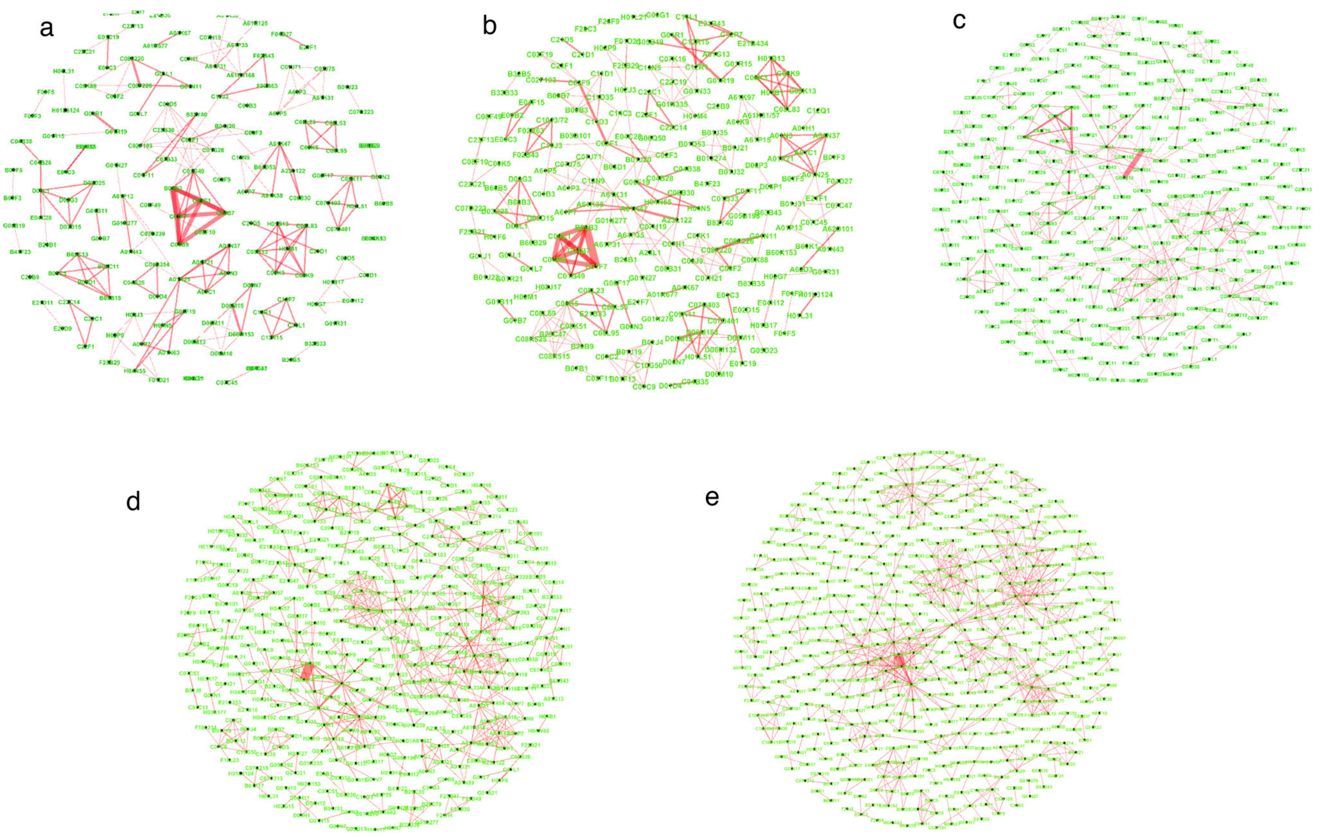

Fig. 6 The evolution of network topology of knowledge network. a Network topology of knowledge network from 2007 to 2011. **b** Network topology of knowledge network from 2008 to 2012. **c** Network topology of knowledge network from 2009 to 2013. **d** Network topology of knowledge network from 2010 to 2014. **e** Network topology of knowledge network from 2011 to 2015.

cooperation, resulting in more concentrated and targeted connections within the collaborative network

Evolution of knowledge network topological structure. The knowledge connection network diagrams with knowledge elements as nodes are extracted, and the five-time periods of 2007–2011, 2008–2012, 2009–2013, 2010–2014, and 2011–2015 are selected, as shown in Fig. 6. The nodes in the knowledge network are not closely connected in 2007–2011 and 2008–2012. In 2009–2013, 2010–2014, and 2011–2015, the distribution of knowledge element nodes in the knowledge network shows a certain degree of gradation. Some nodes are concentrated in the center of the network, and some are at the edge of the network. The knowledge elements in the center of the network are likely to be the core technology in the IUR cooperation, so they have a high frequency of interaction. The knowledge elements at the edge of the network are non-core technology that has little connection with other knowledge, showing a low frequency of interaction.

From 1995 to 2017, the changes in the number of edges, density, clustering coefficient, average shortest path, and network centralization index of the knowledge network are shown in Table 2 above. It can be seen that the number of edges of the knowledge network increases from 14 in 1995–1999 to 3123 in 2013–2017, the average node degree is 0.118 in 1995–1999 and 0.083 in 1996–2000. After a short period of increase, the average node degree decreases. With the increase of innovative subjects and connected edges in the network, the average node degree keeps increasing. The density of the whole network is also gradually decreasing, from 0.156 in 1995–1999 to 0.005 in 2013–2017. The clustering coefficient in the knowledge network increases first and then decreases, which indicates that the character of technology clustering is obvious. The average shortest path has an irregular change, and so does the network centralization index.

Upon integrating the findings of our study, it becomes apparent that different stages of the network's lifespan showcase distinct characteristics. During the formation phase, corresponding to the 2007–2011 and 2008–2012 periods, the nodes within the knowledge network weren't tightly connected, signaling the initial stages of the industry-university-research (IUR) collaboration. As we progressed into the growth phase, covering 2009–2013, 2010–2014, and 2011–2015, the connectivity within the network intensified, leading to a marked increase in interaction frequencies among core technologies. This phase also saw the emergence of clear gradation among knowledge nodes, with central nodes engaging in high-frequency interactions while edge nodes, representing non-core technologies, exhibiting lower frequencies. The maturity phase, spanning from 2012 to 2016, 2013–2017, was characterized by a considerable expansion of the network, with the number of edges surging from 2372 to 3123. Despite the increasing complexity of the network resulting from the influx of diverse knowledge elements and innovative subjects, the density of the network has decreased. This reduction in density indicates the presence of a large and intricate knowledge network. The oscillation of the average shortest path and network centralization index during this period further validates the maturity of the network with varied efficiency and concentration of connections. The study does not present explicit information on the decline or reinvention phase. Drawing upon network lifecycle theories, this phase may potentially exhibit a decline in the network's effectiveness due to oversaturation or redundancy of connections. Alternatively, it could witness a reinvention with

Table 2 Main topological indexes of the knowledge network from 1995 to 2017.

The year	The number of edges	The average node degree	The standard deviation of node degree	The overall network density	Clustering coefficient	The average shortest path	the network centralization index
1995–1999	14	0.118	0.471	0.156	0.778	1.222	0.017
1996–2000	22	0.083	0.400	0.105	0.889	1.154	0.008
1997–2001	24	0.136	0.457	0.100	0.762	1.200	0.009
1998–2002	32	1.100	5.656	0.076	0.833	1.158	0.048
1999–2003	46	0.108	0.649	0.053	0.952	1.148	0.006
2000–2004	58	0.211	0.893	0.049	0.93	1.216	0.006
2001–2005	54	0.242	0.954	0.058	0.93	1.229	0.008
2002–2006	116	0.653	3.014	0.054	0.902	1.372	0.018
2003–2007	206	0.836	3.611	0.041	0.937	1.396	0.01
2004–2008	210	0.577	2.356	0.04	0.949	1.317	0.005
2005–2009	238	0.306	2.434	0.031	0.96	1.201	0.005
2006–2010	362	1.128	5.998	0.021	0.918	1.564	0.004
2007–2011	444	1.485	7.933	0.017	0.894	1.697	0.005
2008–2012	604	3.080	15.553	0.013	0.879	2.130	0.005
2009–2013	994	74.380	351.967	0.010	0.783	5.163	0.04
2010–2014	1442	132.752	687.219	0.008	0.771	5.581	0.054
2011–2015	1740	139.545	710.359	0.007	0.737	5.215	0.048
2012–2016	2372	395.415	1618.525	0.006	0.716	5.632	0.058
2013–2017	3123	512.443	2711.336	0.005	0.364	5.367	0.044

the emergence of new core technologies, potentially triggering a new cycle of growth and maturation. This comprehension of the network's different stages can be instrumental for enterprises, universities, and research institutions in navigating and enhancing their IUR collaborations.

Evolution of inter-organizational technology network topological structure. To observe the changing trend of the relationship in inter-organizational technology networks, we draw the topological structure of the inter-organizational technology network in 2007–2011, 2008–2012, 2009–2013, 2010–2014, and 2011- 2015. The node, such as "H02J3," represents a specific classification code for a patent. It is used to identify and categorize patents based on their subject matter. The node is part of the International Patent Classification (IPC) system, which is used to classify patents based on their technical content.

As can be seen from Fig. 7a, the nodes with a large degree of centrality in the network are State Grid Corporation of China, Tsinghua University, China National Offshore Oil Co., Ltd., CNOOC Research Institute, G01N33, C02F9, C23F1, C02F1, G01R31, G06F19, H02J13, H02J3, and G06Q50. It can be seen from Fig. 7b, that the nodes with a large degree of centrality in the network are State Grid Corporation of China, China National Offshore Oil Co., Ltd., CNOOC Research Institute, H02J3, G01R31, G06Q10, and G06Q50. As can be seen from Fig. 7c, the nodes with a large degree of centrality in the network are State Grid Corporation of China, China Electric Power Research Institute, Jiangsu Electric Power Company, China National Offshore Oil Co., Ltd., G01R31, G06F19, G06Q10, G06Q50, and H02J3. As can be seen from Fig. 7d, the nodes with a large degree of centrality in the network are State Grid Corporation of China, China Electric Power Research Institute, North China Electric Power University, Wuhan University, State Grid Smart Grid Research Institute, State Grid Zhejiang Electric Power Corporation, South China Normal University, Shenzhen Guohua Optoelectronic Technology Co., Ltd., Shenzhen Guohua Optoelectronics Research Institute, G01R31, G06F17, G06F19, G06Q10, G06Q50, and H02J3. It can be seen from Fig. 7e, the nodes with a large degree of centrality in the network include China Electric Power Research Institute, Global Energy Internet Research Institute, State Grid Henan Electric Power Company, North China Electric Power University, South China Normal University, Shenzhen Guohua Optoelectronic Technology Co., Ltd., Shenzhen Guohua Optoelectronics Research Institute, State Grid Corporation of China, G01R31, G06F17, G06Q10, G06Q50, and H02J3. From this, we can learn that no matter in which period, State Grid Corporation of China occupies a very important position. H02J3 and G01R31 are core technologies, which are connected with many nodes in the network. Among them, H02J3 is a circuit device for AC trunk line or AC distribution network, and G01R31 is a test device for electrical performance and a detection device for electrical faults.

From 1995 to 2017, the changes in edge number, network density, average degree, and average shortest path of the inter-organizational technology network are shown in Table 3. It can be inferred that the number of edges of the inter-organizational technology network has increased year by year from 8 edges in 1995–1999 to 6732 edges in 2013–2017. The overall network density experiences a process of first decreasing, then increasing, and finally decreasing. The average degree is 1.600 in 1995–1999 and then changes to 4.125 in 2000–2004 after a short period of increase. After several complex changes, it becomes 4.013 in 2006–2010 and keeps increasing in later periods, which are 4.220, 6.029, 6.956, 7.965, 8.894, 9.585, and 10.221, respectively. The average shortest path of the two-mode network increases first and then decreases, with 2003–2007 and 2005–2009 as the cut-off periods.

The changes in numbers in the evolution of inter-organizational technology network topological structure reflect the dynamic nature of the network. The network is constantly evolving as new nodes (organizations) join and existing nodes leave. The changes in numbers also reflect the changing relationships between the nodes in the network. The progressive increase in the number of nodes over time serves as evidence that more organizations are actively becoming part of this interconnected network. This could be due to a variety of reasons, such as the benefits of collaboration, the need for access to new technologies, or the desire to reduce costs. As more organizations join the network, the network becomes more complex and interconnected. The changes in the number of edges (connections) between nodes in the network reflect the changing relationships between the nodes. As new nodes join the network,

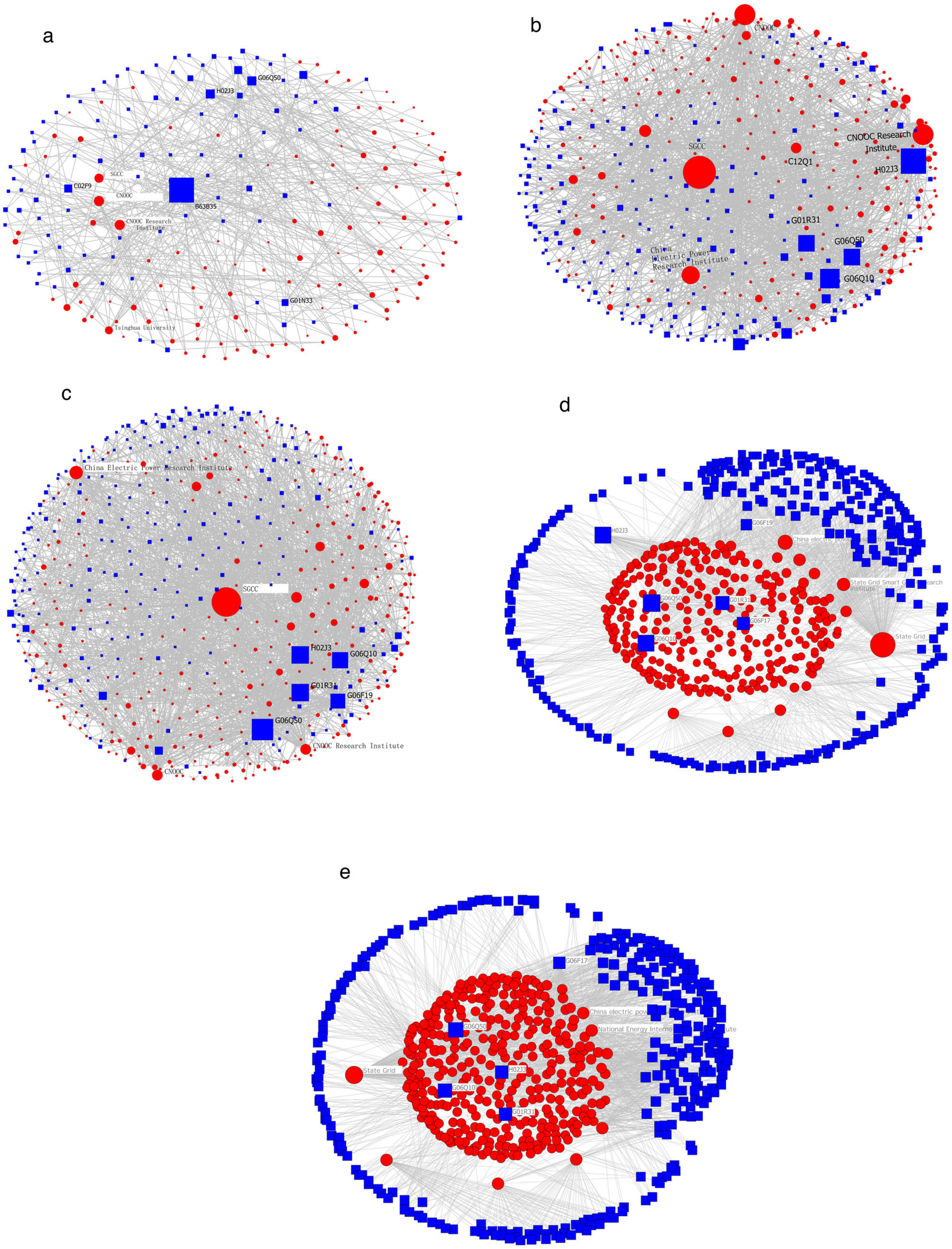

Fig. 7 The evolution of network topology of inter-organizational technology network. **a** Network topology of inter-organizational technology network from 2007 to 2011. **b** Network topology of inter-organizational technology network from 2008 to 2012. **c** Network topology of inter-organizational technology network from 2009 to 2013. **d** Network topology of inter-organizational technology network from 2010 to 2014. **e** Network topology of inter-organizational technology network from 2011 to 2015.

Table. 3 Main topological indexes of inter-organizational technology network from 1995 to 2017.

The year	The number of edges	The overall network density	The average degree	The average shortest path
1995–1999	8	0.178	1.600	1.619
1996–2000	14	0.154	2.000	1.956
1997–2001	26	0.191	3.059	2.397
1998–2002	67	0.113	3.829	2.924
1999–2003	68	0.114	3.886	2.945
2000–2004	66	0.133	4.125	2.966
2001–2005	127	0.059	3.848	4.026
2002–2006	175	0.049	4.118	4.261
2003–2007	110	0.056	3.492	4.758
2004–2008	229	0.028	3.578	4.587
2005–2009	437	0.019	4.065	4.685
2006–2010	600	0.013	4.013	4.622
2007–2011	730	0.012	4.220	4.614
2008–2012	1866	0.010	6.029	3.893
2009–2013	2612	0.009	6.956	3.596
2010–2014	3457	0.009	7.965	3.558
2011–2015	4020	0.010	8.894	3.455
2012–2016	5176	0.009	9.585	3.413
2013–2017	6732	0.009	10.221	3.356

they may form new connections with existing nodes or existing connections may be strengthened or weakened. The number of edges in the network can also be influenced by external factors, such as changes in the market or regulatory environment. The changes in the network's topological structure reflect the changing nature of the relationships between the nodes. For example, the network may shift from a centralized structure, where a few nodes have many connections, to a more decentralized structure, where many nodes have a few connections. This could be due to changes in the goals or strategies of the organizations in the network, or changes in the external environment.

Overall, the variations in numerical values in the development of inter-organizational technology network topological structure demonstrate the dynamic essence of the network and the evolving connections among the nodes. Grasping these transformations can assist organizations in effectively maneuvering through the network and capitalizing on its advantages for fostering innovation and achieving growth. First and foremost, within the inter-organizational technology network of IUR cooperation, it is crucial to emphasize the integration of interdisciplinary approaches across all domains. Additionally, the advancement of industries, particularly strategic emerging sectors, necessitates the collaboration of IUR, extending beyond the confines of academia. On one hand, once enterprises establish cooperative relationships with universities and research institutions, it is essential for them to foster trust, engage in continuous communication, and mutually learn from each other, thereby enhancing the potential for future collaborations. On the other hand, enterprises should proactively pursue partnerships with universities and research institutions, offering them the necessary infrastructure for research and development (R&D), and effectively integrating the resources of these academic and research entities. Such efforts are conducive to promoting the sound and systematic development of relevant industries. Finally, the IUR collaboration innovation system with the enterprise as the main body is not perfect. Enterprises lack the motivation for technological innovation, and the investment in technological research and development is seriously insufficient. At present, only about 11% of innovative enterprises in China have R&D activities[2]. In order to address these challenges, the government needs to implement a top-level design, enhance industrial policies, increase investment in technology research and development, and establish a technology innovation platform for IUR collaboration. These measures will effectively support the research and development of common and key technologies within the industry.

Analysis of the ego network of the IUR collaboration network

The ranking of individual network variables in collaboration networks. In order to delve deeper into the intricacies of collaborative networks, it is critical to turn our attention to Table 4. This table presents an in-depth study of degree centrality and structural hole rankings of diverse organizations operating within these networks across 19 distinct periods from 2000 to 2018. The uniqueness of each period is marked by a notable organization that boasts the maximum degree of centrality or the most expansive structural hole.

During the initial period of 2000–2003, the "superstar" entity in the network, as gauged by the highest degree of centrality, was the China Petroleum and Chemical Corporation. Degree centrality, in network analysis parlance, is a quantitative indicator of the number of direct relationships or links an organization possesses with other organizations within the network. In this sense, the corporation's "superstar" status emerged from its central position and extensive reach within the network.

In the subsequent period of 2004–2007, Zhejiang University came to the fore, exhibiting the highest degree of centrality and thereby establishing itself as the pivotal 'superstar' entity within the network. Its commanding position indicated a high degree of direct collaboration and substantial influence in the network.

The period of 2011–2012 saw another shift in dominance, with the China Electric Power Research Institute securing the highest degree of centrality. From 2013 onwards, the network experienced a duopoly of "superstar" with the State Grid Corporation of China and the China Electric Power Research Institute consistently securing the top two positions in degree centrality rankings. This persistent high ranking further solidified their 'superstar' status within the R&D alliance network.

When the focus shifts to the measure of structural holes, the dynamics of the network change. Structural holes represent the gaps in a network where an organization is positioned to act as a bridge between other organizations. Hence, a high structural hole measure can be interpreted as the organization's ability to control and manipulate the information flow within the network. In the early 2000s, universities and research institutes alternately dominated the top position in the structural holes measure. However, from 2005 to 2010, research institutes consistently surfaced as "superstar", topping the structural hole measure. Subsequently, corporations took the lead in 2011–2013. From 2014 to 2018, the State Grid Technology College consistently emerged as the top organization in structural hole measures, becoming the key "superstar" player in this regard.

These shifting patterns in degree centrality and structural holes offer profound insights into the complex and ever-changing landscape of collaboration networks. The identified "superstar"—be they corporations, universities, or research institutes - occupy pivotal positions within the network. Their influence reverberates through the network, thereby shaping its structural composition, information flow, knowledge creation, and overall trajectory of innovation.

The ranking of individual network variables in knowledge networks. Table 5 offers a comprehensive chronology of the degree centrality and the structural hole metrics in the knowledge network from 2000 to 2018. In this table, each temporal segment

Table 4 Ranking of the individual features of degree centrality and structural hole of collaboration network from 2000 to 2009.

Year	Degree centrality	Structure hole
2000	Sinopec Group, Peking University, Central Iron and Steel Research Institute of the Ministry of Metallurgical Industry, University of Science and Technology Beijing, Beijing Central Engineering and Research Incorporation of Iron and Steel Industry	Yantai University, Sinopec Research Institute of Petroleum Processing, Zhejiang A&F University, Shanghai Institute of Biochemistry of Chinese Academy of Sciences, Zhejiang Haining Silk Group Co., Ltd.
2001	Sinopec Co., Ltd., Sinopec Group, Central Iron and Steel Research Institute of the Ministry of Metallurgical Industry, University of Science and Technology Beijing, Beijing Central Engineering and Research Incorporation of Iron and Steel Industry	Sinopec Research Institute of Petroleum Processing, Zhejiang A&F University, Shanghai Institute of Biochemistry of Chinese Academy of Sciences, Zhejiang Haining Silk Group Co., Ltd., Shenyang Research Institute of Chemical Industry
2002	Sinopec Co., Ltd., East China University of Science and Technology, Central Iron and Steel Research Institute of the Ministry of Metallurgical Industry, University of Science and Technology Beijing, Beijing Central Engineering and Research Incorporation of Iron and Steel Industry	Zhejiang University, Zhejiang A&F University, Shanghai Institute of Biochemistry of Chinese Academy of Sciences, Zhejiang Haining Silk Group Co., Ltd., Sinopec Group
2003	Sinopec Co., Ltd., East China University of Science and Technology, Central Iron and Steel Research Institute of the Ministry of Metallurgical Industry, University of Science and Technology Beijing, Beijing Central Engineering and Research Incorporation of Iron and Steel Industry	Zhejiang University, Zhejiang A&F University, Shanghai Institute of Biochemistry of Chinese Academy of Sciences, Zhejiang Haining Silk Group Co., Ltd., Sichuan University
2004	Zhejiang University, Sinopec Co., Ltd., East China University of Science and Technology, Tsinghua University, Shanghai Jiao Tong University	Shanghai Institute of Microsystem and Information Technology, Fudan University, Shanghai Union Energy Technology Co., Ltd., Sichuan University, Sinopec Research Institute of Petroleum Processing
2005	Zhejiang University, Sinopec Co., Ltd., East China University of Science and Technology, Tsinghua University, Shanghai Jiao Tong University	Sinopec Beijing Research Institute of Chemical Industry, Sinopec Research Institute of Petroleum Processing, Shanghai Institute of Microsystem and Information Technology, Fudan University, Shanghai Union Energy Technology Co., Ltd.
2006	Zhejiang University, Fudan University, Sinopec Co., Ltd., Tsinghua University, Shanghai Jiao Tong University	Sinopec Beijing Research Institute of Chemical Industry, Shanghai Institute of Microsystem and Information Technology, Shanghai Union Energy Technology Co., Ltd., Sinopec Shanghai Research Institute of Petrochemical Technology, Sun Yat-sen University
2007	Zhejiang University, Tsinghua University, Fudan University, Shanghai Jiao Tong University, University of Electronic Science and Technology of China	Shanghai Institute of Microsystem and Information Technology, Shanghai Union Energy Technology Co., Ltd., CapitalBio Corporation, Cancer Institute Chinese Academy of Medical Science, China National Institute of Nano Technology and Engineering
2008	Zhejiang University, Tsinghua University, Fudan University, Shanghai Jiao Tong University, University of Electronic Science and Technology of China	Shanghai Institute of Microsystem and Information Technology, Shanghai Union Energy Technology Co., Ltd., CapitalBio Corporation, Cancer Institute Chinese Academy of Medical Science, China National Institute of Nano Technology and Engineering
2009	China Institute of Water Resources and Hydropower Research, East China University of Science and Technology, Donghua University, Fudan University, Hefei University of Technology	Shanghai Textile Science Research Institute, Shanghai Textile Holding (Group) Co., Ltd, CapitalBio Corporation, Tsinghua University, Cancer Institute Chinese Academy of Medical Science
2010	Sinopec Co., Ltd., Haier Co., Ltd., Qingdao Haier Smart Home Appliance Technology Co., Ltd., Sun Yat-sen University, China Electronics Standardization Institute	Shanghai Textile Science Research Institute, Shanghai Textile Holding (Group) Co., Ltd, CapitalBio Corporation, Tsinghua University, Cancer Institute Chinese Academy of Medical Science
2011	China Electric Power Research Institute, East China University of Science and Technology, Tsinghua University, Sinopec Co., Ltd., Haier Co., Ltd.	Zhangzhou Yichen Magnesite Products Co., Ltd., Shandong Taiguang Electric Co., Ltd., Inner Mongolia Xiangxiang New Building Materials Development Co., Ltd., Xi'an Jiaotong University, Inner Mongolia Changtai Resource Recycling Technology Development Co., Ltd.
2012	China Electric Power Research Institute, South China University of Technology, Tsinghua University, Sun Yat-sen University, State Grid Corporation of China	Zhangzhou Yichen Magnesite Products Co., Ltd., Xinjiang Jiangnan Electric Power Co., Ltd., Wuhan University, Shenzhen Langshi Biological Instrument Co., Ltd., Guangxi Sanjing Chemical Technology Co., Ltd.
2013	State Grid Corporation of China, China Electric Power Research Institute, Tsinghua University, South China University of Technology, East China University of Science and Technology	Zhangzhou Yichen Magnesite Products Co., Ltd., China University of Petroleum (East China), Xinjiang Jiangnan Electric Power Co., Ltd., China University of Petroleum (Beijing), Wuhan University
2014	State Grid Corporation of China, China Electric Power Research Institute, Tsinghua University, North China Electric Power University, Jiangsu Electric Power Company	Jilin University, Northeast Petroleum University, Ocean University of China, Zhangzhou Yichen Magnesite Products Co., Ltd., Xinjiang Jiangnan Electric Power Co., Ltd.
2015	State Grid Corporation of China, China Electric Power Research Institute, North China Electric Power University, Tsinghua University, Jiangsu Electric Power Company	State Grid Technology College, Northeast Petroleum University, Xi'an Shiyou University, State Grid Shaanxi Electric Power Company Economic and Technical Research Institute, Chengdu University of Technology
2016	State Grid Corporation of China, China Electric Power Research Institute, North China Electric Power University, Tsinghua University, Jiangsu Electric Power Company	State Grid Technology College, State Grid Hebei Electric Power Company Economic and Technical Research Institute, Northeast Petroleum University, Xi'an Shiyou University, Xinjiang Jiangnan Electric Power Co., Ltd.
2017	State Grid Corporation of China, China Electric Power Research Institute, North China Electric Power University, Tsinghua University, Xi'an Jiaotong University	State Grid Technology College, State Grid Hebei Electric Power Company Economic and Technical Research Institute, China University of Geosciences(Wuhan), State Grid Inner Mongolia Eastern Electric Power Co., Ltd. Economic and Technical Research Institute, Northeast Petroleum University
2018	State Grid Corporation of China, China Electric Power Research Institute, North China Electric Power University, Tsinghua University, Xi'an Jiaotong University	State Grid Technology College, State Grid Hebei Electric Power Company Economic and Technical Research Institute, Northeast Petroleum University, Xi'an Shiyou University, Xinjiang Jiangnan Electric Power Co., Ltd.

showcases specific knowledge elements that assume superior centrality and possess wide structural holes, effectively serving as the network's "superstar" in their respective periods.

For the initial period spanning 2000 to 2003, the knowledge element C12N15 emerged as a central hub in the network, displaying the highest degree of centrality. Degree centrality, as an indicator of direct ties a node maintains within a network, underlines the influential role of this knowledge element in network interactions. Furthermore, this phase was distinguished by the elements A61K35 and A61K38 which were recorded as having the widest structural holes. The concept of structural holes refers to the 'brokerage' roles these elements perform within the network, controlling information flow and thus significantly impacting knowledge dissemination.

Table 5 Ranking of individual indicators of knowledge network from 1995 to 2018.

Year	Degree centrality	Structural hole
2000	C12N15,A61K35,A61K38,C07C7,C08F112	A61K35,A61K38,C07C7,C08F112,C08F4
2001	C12N15,A61K35,A61K38,C06B45,C06B31	A61K35,A61K38,C06B45,C06B31,C06B23
2002	C12N15,C08F4,A61K35,A61K38,C06B45	A61K35,A61K38,C06B45,C06B31,C06B23
2003	C12N15,C08F10,A61K35,A61K38,C06B45	A61K35,A61K38,C06B45,C06B31,C06B23
2004	H04B17,C12N15,H04B5,H04Q7,A61N1	C12N15,H04B5,H04Q7,A61N1,H04L12
2005	C12N15,H04B17,H04B5,H04Q7,A61N1	H04B5,H04Q7,A61N1,H04L12,C12N5
2006	C12N15,H04B17,C02F3,C02F9,C02F1	C02F3,C02F9,C02F1,H04B5,H04Q7
2007	C12N15,A61P15,C07H17,A61K31,A61P13	C02F3,C02F9,C02F1,H04B5,H04Q7
2008	C12N15,C02F1,A61P15,C07H17,A61K31	C02F11,A01N25,G01N33,H04B5,H04Q7
2009	C02F1,C12N15,A61P15,C07H17,A61K31	C02F11,A01N25,H01B17,A01N63,A01P7
2010	A61K31,A61P15,C07H17,A61P13,A61P9	C12R1,A01N25,C02F3,A61K36,C10L1
2011	C01G49,A61K31,C02F1,A61P15,C07H17	C07D23,D06M15,A61K36,D06M153,E04C3
2012	C02F1,C01G49,A01N25,B09B3,A61P31	C07D23,C02F3,G01N11,D06N7,A61K36
2013	C08K5,C07H1,C08F22,A61K31,B09B3	C14C3,C02F3,C08B30,G01N11,D06N7
2014	C08F22,C08K5,C12R1,H02J3,C08L23	C14C3,H02P21,C02F3,C08B30,G01N11
2015	H02J3,G01R31,C08F22,C08K3,C12R1	C22B9,C14C3,H04L1,G01R21,C08G65
2016	H02J3,G01R31,G06Q50,C12N15,C08F22	H02J15,G05B13,C22B9,G01R21,G06Q30
2017	G01R31,H02J3,C08K3,G06Q50,C08F2	H02J15,G06N99,G01R21,H02P11,C12M1
2018	H02J3,G01R31,C08F22,C08K3,G06Q50	H02J15,G06Q30,G01R21,G08G65,C12M1

Progressing to 2013, the network witnessed a shift in the ‘superstar’ dynamic with a new set of knowledge elements taking the lead. The elements showing the highest degree of centrality during this phase were C08K5, C07H1, C08F22, A61K31, and B09B3, whereas those with the broadest structural holes were C14C3, C02F3, C08B30, G01N11, and D06N7.

By 2017, the ‘superstar’ landscape had once again transformed. The knowledge elements that registered the maximum degree centrality were G01R31, H02J3, C08K3, G06Q50, and C08F2, while those boasting the widest structural holes were H02J15, G06N99, G01R21, H02P101, and C12M1.

Lastly, in 2018, the top echelons of degree centrality included H02J3, G01R31, C08F22, C08K3, and G06Q50, while the elements with the most expansive structural holes were H02J15, G06Q30, G01R21, G08G65, and C12M1.

These empirical findings provide a meticulous dissection of the evolving landscape of the knowledge network. The dynamic shifts in the network’s “superstar” over the years shed light on the structural transformations within the network, the mechanisms of knowledge diffusion, and the pathways of innovation, all of which are significantly influenced by these centrally positioned elements.

The Ranking of the Individual Variables in Inter-organizational Technology Networks. In this illuminating research, the term “superstar” within the landscape of R&D alliance networks, is metaphorically applied to an organization or entity that, over the preceding five-year span, has consistently held a notable stature across various technical domains. Such prestigious status is discerned through a robust, bi-modal network analysis that considers both organizational affiliations and connections between knowledge elements. In essence, the “superstar” is akin to a celestial body with a gravitational pull, extensively fostering collaboration, wielding influence, and making significant contributions to the inception, enhancement, and propagation of technical innovations within the network during the defined epoch.

Delving into Tables 6 and 7, we discern a triadic chronology in the evolution of the R&D alliance networks: The first epoch, dubbed the “formation period” (2000–2010), witnessed the rise of certain “superstars” such as Peking University, Central Iron and Steel Research Institute of the Ministry of Metallurgical Industry, University of Science and Technology, Beijing, alongside technical categories like C12N15, A61K35, A61K38, and others. This period was marked by a shift in the operational pattern from an amalgamation of U-R, I-U, U, R to a more I-centric approach.

The ensuing ‘growth period’ (2011–2014) saw the ascendancy of a new constellation of “superstars” including the China Electric Power Research Institute, East China University of Science and Technology, Tsinghua University, C01G49, A61K31, C02F1, among others. The operational blueprint transformed from a U-R to an I-R matrix. The strategic emerging industry initiative introduced in 2010, backed by the government’s rigorous push for a symbiosis of industry, academia, and research, fostered the prompt implementation of scientific findings, thus, reinforcing the importance of universities and research institutes within the R&D alliance network.

The final phase, termed the “mature period” (2014–2018), spotlighted entities like the State Grid Corporation of China, China Electric Power Research Institute, North China Electric Power University, H02J3, G01R31, C08F22, and others, operating under an I-U-R model. The year 2013 marked a milestone with the first cohort of 14 national collaborative innovation centers, steered by eminent universities, successfully navigating the “2011 plan”, thereby forming the pioneering batch of “2011 plan” entities.

The “2011 Collaborative Innovation Cente” is compartmentalized into four distinct typologies, each catering to a unique focus: the scientific frontier, cultural heritage and innovation, industrial evolution, and regional growth. Each typology serves as a vital pillar, strengthening China’s scientific prowess, boosting national cultural soft power, propelling industrial innovation, and driving regional development.

In the context of the R&D alliance network, there exists a transition from the spotlight on individual “superstars” to recognizing the collective importance of each organization. Particularly in the current Chinese scenario, the focus shifts to the Collaborative Innovation Center for regional development. This center, under local government leadership and focusing on region-specific economic and social advancement, has emerged as a vanguard in promoting regional innovation by synergizing provincial academic institutions with key enterprises or industrialization bases in local staple industries. The prevailing model, I-U-R, underscores the interdependency and equal significance of each component within the network, thereby, heralding a shift from the era of “superstars” to an epoch where every entity plays an integral role in the network’s overall function and progression.

Table 6 The real "superstar" in Formation Stage.

Year	Observation Year	Super Star	Mode	Technology Categories
Formation Stage				
1995–1999	2000	China Electric Power Research Institute; East China University of Science and Technology; Tsinghua University; C01G49; A61K31; C02F1	University, research institute	A61K, C01G, C02F
1996–2000	2001	State Grid Corporation of China; CNOOC Research Institute; China National Offshore Oil Co.,Ltd.; C02F1; C01G49; A01N25	Industry, research institute	A01N, C01G, C01F
1997–2001	2002	State Grid Corporation of China; China National Offshore Oil Co., Ltd.; CNOOC Research Institute; C08K5; C07H1; C08F22	Industry, research institute	C07H, C08F, C08K
1998–2002	2003	State Grid Corporation of China; China Electric Power Research Institute; Jiangsu Electric Power Company; C08F22; C08K5; C12R1	Industry, research institute	C08F, C08K, C12R
1999–2003	2004	Peking University; Central Iron and Steel Research Institute of the Ministry of Metallurgical Industry; University of Science and Technology Beijing; C12N15; A61K35; A61K38	University, research institute	C12N, A61K
2000–2004	2005	Central Iron and Steel Research Institute of the Ministry of Metallurgical Industry; University of Science and Technology Beijing; Beijing Central Engineering and Research Incorporation of Iron and Steel Industry; C12N15; A61K35; A61K38	University, research institute	C12N, A61K
2001–2005	2006	Sinopec Co., Ltd.; East China University of Science and Technology; University of Science and Technology Beijing; C12N15; C08F4; A61K35	Industry, university	C12N, A61K, C08F
2002–2006	2007	Sinopec Co., Ltd.; East China University of Science and Technology; University of Science and Technology Beijing; C12N15; C08F10; A61K35	Industry, university	C12N, A61K, C08F
2003–2007	2008	Zhejiang University; Sinopec Co., Ltd.; East China University of Science and Technology; H04B17; C12N15; H04B5	Industry, university	C12N, H04B
2004–2008	2009	Zhejiang University; Sinopec Co., Ltd.; East China University of Science and Technology; C12N15; H04B17; H04B5	Industry, university	C12N, H04B
2005–2009	2010	Zhejiang University; Fudan University; Sinopec Co., Ltd; C12N15; H04B17; C02F3	Industry, university	C12N, H04B, C02F

Table 7 The real "superstar" in Growth and Mature Stages.

Year	Observation Year	Super Star	Mode	Technology Categories
Growth Stage				
2006–2010	2011	China Electric Power Research Institute; East China University of Science and Technology; Tsinghua University; C01G49; A61K31; C02F1	University, research institute	A61K, C01G, C02F
2007–2011	2012	State Grid Corporation of China; CNOOC Research Institute; China National Offshore Oil Co.,Ltd.; C02F1; C01G49; A01N25	Industry, research institute	A01N, C01G, C01F
2008–2012	2013	State Grid Corporation of China; China National Offshore Oil Co., Ltd.; CNOOC Research Institute; C08K5; C07H1; C08F22	Industry, research institute	C07H, C08F, C08K
2009–2013	2014	State Grid Corporation of China; China Electric Power Research Institute; Jiangsu Electric Power Company; C08F22; C08K5; C12R1	Industry, research institute	C08F, C08K, C12R
Mature Stage				
2010–2014	2015	State Grid Corporation of China; China Electric Power Research Institute; North China Electric Power University; H02J3; G01R31; C08F22	Industry, university, research institute	H02J3, G01R, G08F
2011–2015	2016	State Grid Corporation of China; Global Energy Internet Research Institute; South China Normal University; H02J3; G01R31; G06Q50	Industry, university, research institute	H02J, G01R, G06Q
2012–2016	2017	State Grid Corporation of China; China Electric Power Research Institute; North China Electric Power University; G01R31; H02J3; C08K3	Industry, university, research institute	H02J, G01R, C08K
2013–2017	2018	State Grid Corporation of China; China Electric Power Research Institute; North China Electric Power University; H02J3; G01R31; C08F22	Industry, university, research institute	H02J, G01R, C08F

Conclusion

Discussion and contribution. This comprehensive research leverages the power of a two-mode network analysis methodology to delve into the realm of IUR (Industry, University, and Research institute) collaborative patent data in China. The primary objective is to uncover the intricate tapestry of technology development trajectories and the knowledge flow patterns within IUR collaborations.

One of the pivotal components of this analysis involves isolating "superstar", or key actors who have been instrumental in erecting collaborative networks, knowledge networks, and inter-organizational technology networks in various timeframes. These pivotal actors embody the dynamic ebb and flow of technology trends, acting as the cornerstone of this interconnected ecosystem.

Through exhaustive data analysis, we discern that as the roster of innovation organizations and the nexus of connected edges within the network expands, the average node degree correspondingly elevates. Paradoxically, there is a gradual ebbing of the overall network density, dipping from 0.156 in the period 1995–1999, to a paltry 0.005 in 2013–2017. Furthermore, the clustering coefficient within the knowledge network initially escalates, followed by a gradual deflation, indicative of a pronounced predilection for technology clustering. Metrics like the average shortest path and the network centralization index illustrate an erratic trend, eschewing linearity.

Specific periods such as 2009–2013, 2010–2014, and 2011–2015 reveal a distinct hierarchical stratification in the distribution of knowledge element nodes within the knowledge network. Core technologies gravitate towards the network's epicenter, indicative of their high interaction frequency, given their strategic positioning within the IUR collaboration. Conversely, nodes on the network's periphery correspond to non-core technologies, which due to their isolated positioning, exhibit limited interaction with the network.

Across all temporal phases, the State Grid Corporation of China emerges as a steadfast "superstars", firmly ensconced in a dominant position within the network. Core technologies such as H02J3 and G01R31 have forged strong connections with an array of nodes within the R&D alliance network. It is noteworthy that H02J3 pertains to an AC circuit device engineered for trunk lines or distribution networks, while G01R31 is a device specifically designed for electrical performance testing and fault detection.

The evolution of the R&D alliance network traverses three distinct stages. The first stage, stretching from 2000 to 2010, delineates the formative phase where the operational pattern transmuted from U-R, I-U, U, R to I. The second phase, spanning from 2011 to 2014, signals a growth stage and witnessed a mode shift from U-R to I-R. The final stage, extending from 2014 to 2018, signifies a maturation phase, where the operational mode stabilizes at I-U-R. An analysis of the ego network reveals no fixed "superstars". Instead, leadership roles are not static and are shared by different types of nodes.

A comparative analysis of developed and developing nations unearths profound disparities in their technological innovation capabilities. Developed nations, equipped with avant-garde technology and robust legal and intellectual property protection mechanisms, engender a conducive environment for IUR cooperation. In these countries, robust collaboration amongst enterprises, universities, and research institutions catalyzes the efficient translation and application of scientific and technological achievements. In stark contrast, developing nations grapple with significant challenges in technological innovation, attributable to a lower level of scientific and technological development, inadequate capabilities for converting scientific and technological achievements, and underdeveloped legal and intellectual property protection mechanisms.

A salient differential between the R&D alliance networks of developed and developing countries lies in their respective proficiencies for result transformation. Developed countries, boasting sophisticated mechanisms for technology transfer and commercialization, facilitate seamless conversion of research outcomes into commercial value, thereby fostering the integration of technological innovation with economic development. In contrast, developing countries are beleaguered by hurdles such as sub-optimal technology transfer and commercialization mechanisms, insufficient funding, talent dearth, and a lack of effectiveness in applying research outcomes. These impediments hamper the pace of technological innovation and economic development. Moreover, developed countries possess a well-entrenched intellectual property protection system and legal regulations that stimulate innovation and facilitate technology transfer. Conversely, the intellectual property protection mechanisms and legal systems in developing nations are still nascent, and intellectual property infringement is rampant, further stymieing technological innovation and transformation.

Policy implications. The above discussions provide some insights into the R&D alliance networks in China for the IURC. Firstly, in the era of knowledge economy sharing, it is important for the government to focus on interdisciplinary initiatives and applications in all fields, with the principles of openness, environmental friendliness, coordination, and sustainability, in order to strengthen the two-mode network of IUR collaboration. Secondly, the development of industries, especially strategic emerging industries, requires collaboration between IUR and not just universities. Enterprises that have established cooperative relationships with universities and research institutions should enhance trust, maintain continuous communication, and foster mutual learning, in order to sustain long-term collaborative partnerships. On the other hand, enterprises actively seeking collaboration opportunities with universities and research institutions should establish adequate infrastructure and create a conducive academic atmosphere for R&D collaboration. They should also effectively absorb and integrate the resources of universities and research institutions, which will contribute to the healthy and orderly development of relevant industries. Lastly, the current IUR collaboration innovation system, with enterprises as the main players, is not perfect. Enterprises lack the motivation for technological innovation, and investment in technological research and development is seriously inadequate. Currently, only about 11% of innovative enterprises in China engage in R&D activities. The government should refine industrial policies through top-level design, increase investment in technology research and development, and establish a technology innovation platform for IUR collaboration, in order to support the research and application of diverse core technologies in the industry.

Limitations and future research directions. Although this study has significant theoretical and practical implications, it also has several limitations that could be explored in future research. First, the present data are from the IURC Project of SIPO, which can be further excavated for other databases such as WIPO, UPSTO, and EPO. Second, this study analyzes a two-mode network. In an actual situation, the innovation organization will be embedded in a multi-modal environment, such as the country, the region, the innovation organization's internal environment, the innovation organization's external environment, the innovation organization's internal knowledge, and the innovation organization's external knowledge. Research on multi-mode environments can be retrieved in future research. Third, the research on two-mode networks needs to be further expanded. The innovative significance given by the attributes of different galaxies will break new ground for us to explore in the network. Fourth, there are many factors that have not been considered in the study, and the research indicators need to be further supplemented in the future, such as network diameter, network efficiency, block model of the network, connectivity of the network, and the small-world network model and so on. Finally, our current study is concerned with networks of a substantial scale and different time durations. However, to distinguish the true evolution of the empirical network structure from the random network, there is a way to design a benchmark network by controlling the number of nodes and edges of the network and then comparing the structure between the random network and the empirical network. In future work, we will be examining the discrepancies between the real-world networks and simulated networks.

Data availability

All data generated or analyzed during this study are included in this published article and its supplementary information files.

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Notes

1 Caltech, Stanford, Berkeley, and other world-renowned universities near the Silicon Valley Science and Technology Park; MIT, Harvard and Boston University near the Route 128 High Tech Park in Boston; Atlanta University and Georgia Institute of Technology near the Atlanta Hi-Tech Park; the Triangle Technology Park based on North Carolina State University, Duke University in Durham and the University of North Carolina in Chapel Hill, etc.

2 National Bureau of Statistics of China. (2019). Statistical Communique of the People's Republic of China on the 2018 National Economic and Social Development. Retrieved from http://www.stats.gov.cn/english/PressRelease/201903/t20190301_1651248.html.

References

Ahuja G (2000) Collaboration networks, structural holes, and innovation: a longitudinal study. Admin Sci Q 45:425–455

Arora A, Belenzon S, Patacconi A (2018) The decline of science in corporate R& D. Strategic Manag J 39:3–32

Atasoy H, Chen PY, Ganju K (2018) The spillover effects of health IT investments on regional healthcare costs. Manag Sci 64:2515–2534

Berardo R (2014) Bridging and bonding capital in two-mode collaboration networks. Policy Stud J 42:197–225

Boccaletti S, Bianconi G, Criado R, Del Genio CI, Gómez-Gardenes J, Romance M, Sendina-Nadal I, Wang Z, Zanin M (2014) The structure and dynamics of multilayer networks. Phys Rep 544:1–122

Carnabuci G, Bruggeman J (2009) Knowledge specialization, knowledge brokerage and the uneven growth of technology domains. Social Forces 88(2):607–641

Carnabuci G, Operti E (2013) Where do firms' recombinant capabilities come from? Intraorganizational networks, knowledge, and firms' ability to innovate through technological recombination. Strategic Manag J 34(13):1591–1613

Chang SH (2017) The technology networks and development trends of university-industry collaborative patents. Technol Forecasting Soc Change 118:107–113

Chen P, Tong R, Yu B, Wang Y (2020) Reliable shortest path finding in stochastic time-dependent road network with spatial-temporal link correlations: A case study from Beijing. Expert Syst Appl 147:113192

Choe H, Lee DH (2017) The structure and change of the research collaboration network in Korea (2000–2011): Network analysis of joint patents. Scientometrics 111:917–939

Cohen WM, Levinthal DA (1989) Innovation and learning: the two faces of R & D. Econ J 99:569–596

Connolly WE (2005) Pluralism. Duke University Press, Boston

Dibiaggio L, Nasiriyar M, Nesta L (2014) Substitutability and complementarity of technological knowledge and the inventive performance of semiconductor companies. Res Policy 43(9):1582–1593

Dyer JH, Hatch NW (2006) Relation-specific capabilities and barriers to knowledge transfers: creating advantage through network relationships. Strategic Manag J 27:701–719

Feldman MP, Kelley MR (2006) The ex ante assessment of knowledge spillovers: Government R & D policy, economic incentives and private firm behavior. Res Policy 35:1509–1521

Fleming JS, Sorenson RL (2001) Measurement of cognitive, affective, and behavioral dimensions of job satisfaction. J Vocational Behav 58:97–127

Flipo C, Mannucci PV, Yong K (2023) The impact of cultural tightness on the relationship between structural holes, tie strength, and creativity. J Int Bus Stud 54(2):332–343

Gilding M, Brennecke J, Bunton V, Lusher D, Molloy PL, Codoreanu A (2020) Network failure: biotechnology firms, clusters and collaborations far from the world superclusters. Res Policy 49:103902

Guan J, Liu N (2015) Invention profiles and uneven growth in the field of emerging nano-energy. Energy Policy 76:146–157

Guan J, Liu N (2016) Exploitative and exploratory innovations in knowledge network and collaboration network: a patent analysis in the technological field of nano-energy. Res Policy 45:97–112

Guo M, Yang N, Wang J, Zhang Y, Wang Y (2021) How do structural holes promote network expansion? Technol Forecasting Soc Change 173:121129

Hanaki N, Nakajima R, Ogura Y (2010) The dynamics of R & D network in the it industry. Res Policy 39:386–399

Hershberg E, Nabeshima K, Yusuf S (2007) Opening the Ivory Tower to business: University–Industry linkages and the development of knowledge-intensive clusters in Asian cities. World Dev 35(6):931–940

Hou H, Kretschmer H, Liu Z (2008) The structure of scientific collaboration networks in scientometrics. Scientometrics 75:189–202

Iammarino S, McCann P (2006) The structure and evolution of industrial clusters: Transactions, technology and knowledge spillovers. Res Policy 35:1018–1036

Jaffe AB (1986) Technological opportunity and spillovers of R & D: evidence from firms' patents, profits and market value. Am Econ Rev 76:984–1001

Kafouros M, Wang C, Piperopoulos P, Zhang M (2015) Academic collaborations and firm innovation performance in China: the role of region-specific institutions. Res Policy 44:803–817

Kang KN, Park H (2012) Influence of government r & d support and inter-firm collaborations on innovation in Korean biotechnology SMES. Technovation 32:68–78

Kumar P, Zaheer A (2019) Ego-network stability and innovation in alliances. Acad Manag J 62(3):691–716

Laumann EO, Galaskiewicz J, Marsden PV (1978) Community structure as interorganizational linkages. Annu Rev Sociol 4:455–484

Laursen K, Salter A (2006) Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. Strategic Manag J 27:131–150

Liang X, Liu AM (2018) The evolution of government sponsored collaboration network and its impact on innovation: A bibliometric analysis in the Chinese solar PV sector. Res Policy 47:1295–1308

Lyu L, Wu W, Hu H, Huang R (2019) An evolving regional innovation network: collaboration among industry, university, and research institution in China's first technology hub. J Technol Transfer 44:659–680

Markov NT, Ercsey-Ravasz M, Van Essen DC, Knoblauch K, Toroczkai Z, Kennedy H (2013) Cortical high-density counterstream architectures. Science 342(6158):1238406

Menéndez-Manjón A, Moldenhauer K, Wagener P, Barcikowski S (2011) Nano-energy research trends: bibliometrical analysis of nanotechnology research in the energy sector. J Nanopart Res 13:3911–3922

Mina A, Bascavusoglu-Moreau E, Hughes A (2014) Open service innovation and the firm's search for external knowledge. Res Policy 43:853–866

Moldavanova AV, Akbulut-Gok I (2022) Inter-organizational networking and the Great Recession: Lessons from Detroit arts and culture organizations. Int J Publ Admin 45(3):213–227

O'Mahony M, Vecchi M (2009) R & d, knowledge spillovers and company productivity performance. Res Policy 38:35–44

Palit S, Hora M, Ghosh S (2022) Global buyer–supplier networks and innovation: The role of technological distance and technological breadth. J Oper Manag 68(6-7):755–774

Papanastassiou M, Pearce R, Zanfei A (2020) Changing perspectives on the internationalization of r & d and innovation by multinational enterprises: a review of the literature. J Int Bus Stud 51:623–664

Park H, Yoon J (2014) Assessing coreness and intermediary of technology sectors using patent co-classification analysis: the case of Korean national R&D. Scientometrics 98:853–890

Paruchuri S, Awate S (2017) Organizational knowledge networks and local search: the role of intra-organizational inventor networks. Strategic Manag J 38:657–675

Pepe A (2011) The relationship between acquaintanceship and coauthorship in scientific collaboration networks. J Am Soc Inform Sci Technol 62:2121–2132

Phelps CC (2010) A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. Acad Manag J 53:890–913

Qianqian L, Yijun L (2020) The China-Pakistan economic corridor: the Pakistani media attitudes perspective. Technol Soc 62:101303

Qiu S, Liu X, Gao T (2017) Do emerging countries prefer local knowledge or distant knowledge? spillover effect of university collaborations on local firms. Res Policy 46:1299–1311

Reagans R, McEvily B (2003) Network structure and knowledge transfer: The effects of cohesion and range. Admin Sci Q 48:240–267

Schot J, Steinmueller WE (2018) Three frames for innovation policy: R & D, systems of innovation and transformative change. Res Policy 47:1554–1567

Shijaku E, Ritala P (2023) Behavioral antecedents of firm's ego-network competitiveness: the case of the global pharmaceuticals. Long Range Planning 56(3):102308

Snijders TA, Van de Bunt GG, Steglich CE (2010) Introduction to stochastic actor-based models for network dynamics. Soc networks 32(1):44–60

So MK, Chu AM, Chan TW (2021) Impacts of the COVID-19 pandemic on financial market connectedness. Finance Res Lett 38:101864

Sprong N, Driessen PH, Hillebrand B, Molner S (2021) Market innovation: a literature review and new research directions. J Bus Res 123:450–462

Stojčić N (2021) Collaborative innovation in emerging innovation systems: evidence from Central and Eastern Europe. J Technol Transfer 46(2):531–562

Tortoriello M, Reagans R, McEvily B (2012) Bridging the knowledge gap: The influence of strong ties, network cohesion, and network range on the transfer of knowledge between organizational units. Organization Sci 23:1024–1039

Vo TT, Nezamabadi S, Mutabaruka P, Delenne JY, Radjai F (2020) Additive rheology of complex granular flows. Nat Commun 11(1):1476

Vom Stein N, Sick N, Leker J (2015) How to measure technological distance in collaborations—The case of electric mobility. Technol Forecasting Soc Change 97:154–167

Wang C, Rodan S, Fruin M, Xu X (2014) Knowledge networks, collaboration networks, and exploratory innovation. Acad Manag J 57:484–514

Wasserman S, Faust K (1994) Social network analysis: methods and applications. Cambridge University Press

Wen J, Qualls WJ, Zeng D (2021) To explore or exploit: the influence of inter-firm R&D network diversity and structural holes on innovation outcomes. Technovation 100:102178

Xia C, Li C (2023) Art of saying no: linking trust structural hole to knowledge hiding and creativity. Asia Pac J Manag 1–35

Yang J, Zhang J, Zeng D (2022) Scientific collaboration networks and firm innovation: the contingent impact of a dynamic environment. Manag Decis 60(1):278–296

Yang W, Yu X, Wang D, Yang J, Zhang B (2021) Spatio-temporal evolution of technology flows in China: Patent licensing networks 2000– 2017. J Technol Transfer 46:1674–1703

Yuan MM, Guo X, Wu L, Zhang YA, Xiao N, Ning D, Zhou J (2021) Climate warming enhances microbial network complexity and stability. Nat Clim Change 11(4):343–348

Zhang J, Jiang H, Wu R, Li J (2019) Reconciling the dilemma of knowledge sharing: a network pluralism framework of firms' r & d alliance network and innovation performance. J Manag 45:2635–2665

Zhao Y, Qi N, Li L, Li Z, Han X, Xuan L (2023) How do knowledge diversity and ego-network structures affect firms' sustainable innovation: evidence from alliance innovation networks of China's new energy industries. J Knowl Manag 27(1):178–196

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Author contributions

ZX: Conceptualization, Methodology, Software, Formal Analysis, Writing—Original Draft; LW: Data Curation, Conceptualization, Funding Acquisition, Visualization, Writing—Review & Editing; DF: Supervision, Investigation, Validation.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informal consent

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Additional information

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