Journal of Digital Economy 2 (2023) 64–80

Contents lists available at ScienceDirect

Journal of Digital Economy

journal homepage: www.keaipublishing.com/en/journals/journal-of-digital-economy

Research article

The influence factors of innovation networking formation based on ERGM: Evidence from the smart medical industry

Chao Lu, Bin Li *

School of Management, Shanghai University, China

A R T I C L E I N F O

Keywords:
ERGM
Smart medical industry
Innovation network
Influence factors

A B S T R A C T

With the growth of the social economy and technology, innovation networks have emerged as one of the most significant methods for analyzing the evolution of industrial innovation. Yet, there is a shortage of studies analyzing the components that influence network creation. By highly integrating digital technology with the traditional medical industry chain, the smart medical industry has become one of the important sectors of the digital economy. With the advent of internet-based diagnosis and treatment technologies, innovation inside the smart medical industry has taken the form of a network. This study aims to construct an innovation network by organizing and analyzing patent data from China's smart medical industry cooperation, covering the period from 2005 to 2022. The data is sourced from the IncoPat database. The analysis utilizes the Exponential Random Graph Model (ERGM) approach to conduct regression analysis on various factors. These factors include endogenous structural characteristics, node feature variables such as node emergence time and institutional attributes, as well as the distance network and IPC attribute network. By examining the driving mechanism and influence mechanism that influence the innovation network, this study contributes to the smart medical industry research by gaining a better understanding of the current status of innovation network, which can be advantageous for businesses in this field to accurately recognize and actively promote their innovation practices.

1. Introduction

The innovation network is formed through innovation cooperation between innovation subjects (C F, 1991). The enterprise innovation model revolves around the innovation network, as organizations seek a competitive advantage through innovation and creativity (Zeng and Liefner, 2019). Previous research on innovation networks has predominantly focused on high-tech industries characterized by significant technological content, high output value of new products, and a strong demand for innovation and collaboration (Cao et al., 2022). The existing literature on innovation networks primarily explores two aspects: the form and characteristics of innovation cooperation networks, including network structure and performance; and the evolution and influencing factors of cooperative innovation networks (Muller and Peres, 2019; Powell et al., 2005; Bathelt and Buchholz, 2019). However, there remains a need for further research on the impact of innovation network structure on cooperation relationships in networks. Moreover, few literatures combine these influence factors: network structure and external factors (Zhao et al., 2020).

The reason for this phenomenon is the mature methods which dominate the research on innovation network formation and influencing factors, for example, Gravity Model, Negative Binomial Regression and Quadratic Assignment Procedures (QAP), ignores the

* Corresponding author. 20 Chengzhong Road, Jiading District, Shanghai, 200444, China.
E-mail addresses: 06luchao@163.com (C. Lu), lib15138@shu.edu.cn (B. Li).

https://doi.org/10.1016/j.jdec.2023.06.001
Received 28 February 2023; Received in revised form 12 June 2023; Accepted 13 June 2023

influence of network structure, such as triangle structure and endogeneity, on the formation of network connection, which leads to excessive attention on the impact of proximity on innovation network (Gui et al., 2019; Liang et al., 2022; Pan et al., 2020). Considering the ability to simultaneously model and compare actor-level attributes against contextual network effects (He et al., 2019), the Exponential random graph models (ERGM) have emerged as a probabilistic network model parameterized by sufficient statistics based on structural properties (YaveroğluÖ et al., 2015). This model assumes that network relationships are generated by stochastic processes, which has become an essential method in researching network influencing factors in recent years. ERGM provides a framework for analyzing network formation and is widely used in industrial innovation and development research.

The utilization of 5G technology, artificial intelligence, and the Internet of Things in the smart medical industry enables the fulfillment of essential functions such as remote diagnosis, medical data mining, electronic medical guidance, and intelligent assisted diagnosis and treatment. This technological support has brought about a new form of digitalization in the medical system, which can fundamentally enhance Chinese industrial systems and foster the development of business ecosystems (Shi et al., 2022). Since 2017, China's smart medical device market has experienced rapid growth, accompanied by a continuous increase in the size of the industry (as depicted in Fig. 1).

With the growth of the smart medical industry, the few linked studies on the subject have mostly concentrated on technology development and policy recommendations (Wang et al., 2021a). However, few quantitative studies have been done on the growth or innovation of the smart medical business as it currently stands (Zhang et al., 2022a). Liu and Yang (2018), Liu and Lyu (2020), and other scholars have demonstrated that China's strategic emerging industries, including the smart medical industry, have formed an innovation network structure. Knowledge sharing benefits from network contact between participants, which encourages innovation (Laursen et al., 2012). There are few studies that identify the innovation network of China's smart medical industry from the perspective of patent collaboration, despite the fact that innovation networks are crucial to the development of industries. Furthermore, thorough research on the procedures and influencing variables that led to the development of China's smart medical sector innovation network is still absent. According to Zhang and Rao (2021a), there is still a barrier preventing the growth of the smart medical industry in our nation due to the poor invention capacities of businesses and the lack of cooperative innovations among many disciplines.

This paper will attempt to answer the following three questions:

*Q*1: What network is built through collaborative innovation on smart medical industry innovation? What are its structural features?
*Q*2: What factors can influence the formation of connections within an innovation network of the smart medical industry?
*Q*3: How do these factors affect the formation of innovation network of the smart medical industry?

The above missions will be accomplished in the following ways: related forms of data, such as the number of patents data on innovation cooperation in China's smart medical industry, were obtained from the database named IncoPat in order to form the innovation network in the smart medical industry. The innovation network is constructed using social network analysis, such as network density and degree centrality, which were investigated using software called Ucinet 6.0. Then, the corresponding variables are selected, and their influencing mechanism is hypothesized according to the literature. Finally, the influencing mechanisms of innovation networks were analyzed using ERGM.

2. Literature review

2.1. Innovation network

2.1.1. The definition of innovation network

As early as 1991, Freeman took the lead in defining the innovation network, believing that it is an institutional arrangement of enterprise-to-enterprise innovation cooperation, and divided the innovation network into different types of collaboration(C F, 1991). Lundvall (2007) found that innovation participants can form a network structure through various connections and influence innovation

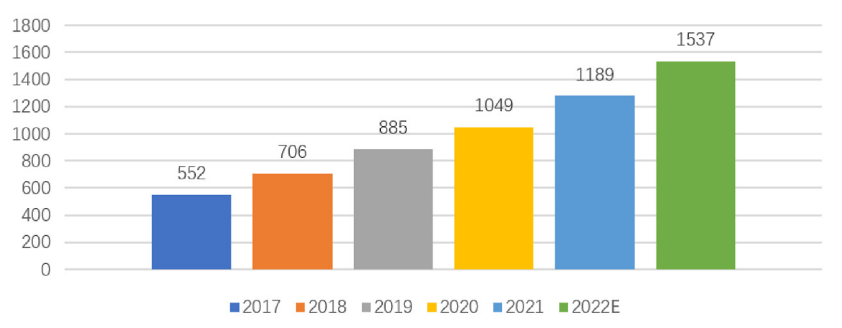

Fig. 1. Scale of China's smart medical industry investment from 2017 to 2022
(Unit: RMB 100 million).
Data source：www.askci.com

activities. As a result, the innovation network is defined as the networking behavior of innovation participants during the innovation process. The notion of innovation network is often defined according to two complementary functional and morphological perspectives. Combining the above two types of definitions (Desmarchelier et al., 2020), the innovation network is a collaborative group in which various innovators collaborate in the formation and development of innovative products (Ahrweiler and Keane, 2013).

Innovation networks under this definition have obvious synergistic characteristics and can achieve overall benefits greater than the sum of individual benefits. Participating in well-functioning innovation networks brings benefits to all actors. The R&D collaboration-based innovation network among enterprises in many high-tech industries, such as computers, semiconductors, telecommunications, and medicine, has become an important means of realizing innovation (Wang et al., 2021b).

As the scholarly understanding of the innovation process changes, so do the main subjects in innovation networks. Owing to theoretical and data limitations, the early research on innovation networks only defined the subjects as corporate institutions and enterprises. With the advancement of innovation network research, the subjects of innovation network are being expanded to include all subjects involved in innovation activities, such as governments, enterprises, scientific research institutions and service guarantee departments (Li et al., 2021). The main subjects of the innovation network that will be used in this paper are a number of enterprises, hospitals, scientific research institutions, and other departments that can participate in patent cooperation applications, such as medical institutions in the smart medical industry's innovation process, digital medical equipment providers providing smart medical applications and smart medical equipment, and medical regulatory agencies managing smart medical institutions.

2.1.2. The influence factors of the evolution of innovation network

Understanding the underlying mechanism that influences the emergence of network edges poses a significant challenge in the analysis of network modeling. The formation of an innovation network is influenced by three distinct categories of factors.

Firstly, external characteristics, such as node properties, impact the propensity of nodes to establish connections with others (Zhang et al., 2022b). These characteristics include attributes like node participation time and organizational attributes. Fan et al. (2021) propose that variations in the development and functioning of innovation subjects may result in disparities in networking activities. Zeng et al. (2011) found that enterprises with excellent intermediary serviceability, in the stage of rapid development, large scale, and the same ownership model are more likely to have innovation cooperation through their analysis of enterprise innovation cooperation in Shanghai Zhangjiang High-Tech Park. Organizations with a technology-driven development strategy are more likely to engage in innovative collaboration (Wei et al., 2010). However, it is essential to conduct case-specific analyses as innovation networks in different industries exhibit diverse fundamental attributes and connection mechanisms.

The analysis of innovation networks encompasses the significant role played by multidimensional closeness between nodes, which motivates their pairing. Extensive discussions have taken place regarding various types of proximity, including geographical, cognitive, organizational, cultural, and institutional proximity (Teng et al., 2021). Chinese scholars have also argued that reducing cognitive distance and the gap in scientific productivity between parties strengthens their relationship (Brennecke and Rank, 2017).

Both the node attribute based on innovation agents and the side attribute based on inter-agent relationships, such as proximity, only consider exogenous elements that influence network development and evolution. Scholars have acknowledged that the generation and evolution of networks can be influenced by the internal dynamics of local Network Configuration, such as transitivity and preferred links (Kaplan and Tripsas, 2008). The third type consists of the network's internal features, also known as network effects, which are created by the interdependence between connections and result in the construction of local structures that are more complicated than the formation of individual edges (Hazir and Autant-Bernard, 2014). These include overall network density measured by the number of edges, the transitivity effect assessed by the geometrically weighted edgewise shared partner distribution, and the edgewise shared partner distribution (Gwesp). Furthermore, there are three higher-order terms: alternating 2-paths, alternating k-triangles, and alternating k-stars (Ji et al., 2022). Vinciguerra and Frenken et al. (2010) suggested that subjects with more partners are more likely to attract new ones, demonstrating a one-to-many K-star configuration, also known as the preferred link or preferred attachment effect in network creation.

Invention activities vary greatly amongst industries. Therefore, innovation networks of various industry types and spatial dimensions have vastly diverse structural features, levels of efficiency, and evolution rules (Qin and Gang, 2014). Through product research and development and company data in the mobile health industry, Onodera and Sengoku (2018) found that government regulatory measures, such as the formulation of laws and regulations and the clarification of standards related to medical devices, had a positive impact on industrial innovation. Bessant et al. (2017) studied the inclusive characteristics in the innovation process of the digital healthcare industry from the perspective of responsible innovation.

With the advancement of the development of the smart medical industry, the relevant qualitative analysis literature on the influence factors of industrial innovation is quite scarce, resulting in the lack of a theoretical basis for the formulation of industry-related policies and the lack of reference data for enterprise strategic plans, which seriously restricts the development of industrial innovation.

2.2. Exponential random graph model

2.2.1. The advantages of ERGM

The exponential random graph model (ERGM) is a well-established statistical approach to modelling social network data used to analyze the influencing factors and mechanisms. he conventional interpretation of the ERGM results focuses on the network-level implications of the connection of the network. Specifically, the advantages of ERGM advantages are as follows.

Above all, the adaptability of the ERGM method is exemplified by the fact that it allows scholars to directly derive the probability distribution at the network level (Zhang et al., 2021a), with very few limits on the structure of networks that may be utilized to conduct an ERGM analysis. It indicates the allowance of ERGM for arbitrarily complex network structures to be modeled and any network relationship problems to be assessed (Xu et al., 2023).

Then, ERGM allows for the creation of a comprehensive model of the network's state through a process that is significantly distinct from regression. As the observed network is seen as a single instance from a multivariate distribution, there is no need to assume independence between actors or connections within the network (Cranmer and Desmarais, 2011). Thus, its modeling flexibility to examine variables with relationship interdependence is remarkable.

Importantly, ERGM evaluates not only the qualities of the nodes themselves but also the influence of the network's internal structure, which can show the influencing variables and the mechanism of the network development in a more comprehensive way (Cao et al., 2019).

Existing researches mostly use the Quadratic Assignment Program (QAP) technique, the Stochastic Actor-Oriented Model (SAOM), and ERGM to model and study the influencing elements on the establishment of regional industrial innovation networks. These models assist individuals in comprehending how the ties and structure of a network arise.

Distinguished from general statistical methods, the QAP method primarily relies on the relationship between variables and utilizes a matrix network as both the explanatory and dependent variables. On the other hand, SAOM serves as a statistical model for network panel data. It effectively addresses issues of multicollinearity and structural autocorrelation and can simulate the impact of endogenous structural effects, similarity, and node attributes on network evolution (Block et al., 2016). SAOM has been applied to analyze the spatial dynamics of global and regional knowledge networks (Balland et al., 2016).

The primary advantage of ERGM and QAP over conventional models is that they assume that the existence of a particular tie within the network predicts the existence of certain other ties within the network (Hermans, 2021). Whereas standard models assume there is no interaction, which makes it more advantageous for evaluating complex network structures consisting of multiple stakeholders (Zhang et al., 2021b). In addition, SAOM hypothesizes that the change from one state to another, says dynamics, results from the micro decisions of actors to access the business or technical knowledge of others, indicating that ERGM models focus on the structure of social networks, whereas SAOM models focus on the behavior of individuals (Block et al., 2016).

In conclusion, this paper employs ERGM to examine the evolution process and affecting aspects of the innovation network in the smart medical business.

2.2.2. The application of ERGM

ERGMs were first applied in the field of economic geography, as indicated by Maggioni and Uberti (2011). As an econometric model of complex networks, ERGM can be used in many industries, such as the biotech industry, public and private hospitals, the aerospace industry, high-tech to cultural goods cluster, life sciences, etc. ERGM is used, for instance, to examine the reciprocity impact, transmission mechanism, and structure extension mechanism in the creation of teenage peer networks in social networks (Schierjott et al., 2018; Broekel and Hartog, 2013; Jiao et al., 2017). Besides, Snijders (2001) demonstrated that some kinds of ERGM can arise from the dynamic decision-making process among boundedly rational agents.

However, there is a dearth of studies employing this model to investigate the formation process of innovation networks in the smart medical industry. Considering the advantages of ERGM and the existing research landscape, this study utilizes the exponential random graph model to uncover the underlying mechanisms driving the formation of patent cooperation networks in the smart medical industry. Additionally, it comprehensively examines the impact of various factors, including network structure, applicant attributes, and patent application time, on the emergence of innovation networks in the smart medical industry.

2.3. Digital economy and smart medical industry

The digital economy has witnessed rapid evolution, particularly in developing countries, due to its ability to greatly enhance resource and labor efficiency (Bukht and Heeks, 2018). Since the 2016 G20 Initiative on Digital Economy Development and Cooperation, research on the digital economy has experienced substantial growth, with a focus on defining its key elements, important vectors, and effective drivers (Ren et al., 2022). The Chinese government has implemented significant policies to promote the digital economy, including the Digital Transformation Partnership Initiative aimed at accelerating its development.

The digital economy generates value by analyzing behavioral data obtained from tracking daily digital activities and employing intelligent analytics. It plays a crucial role in various sectors, including medicine (Schiavone et al., 2021). Electronic medical records, imaging, pharmacy records, and laboratory data are essential for the smart medical industry (Monteith and Glenn, 2016). According to IBM, a majority of medical data will be generated from health apps, patient monitoring, and behavioral data obtained through daily digital transactions.[1]

The smart medical industry leverages technology to enhance healthcare quality. By integrating medical technology, artificial intelligence, and data analytics, it aims to improve patient outcomes, reduce healthcare costs, and enhance the efficiency of healthcare delivery. H. D(2013) categorized the digital healthcare industry into four segments: telemedicine, mobile health, health analytics, and digital healthcare systems. Technologies employed in the smart medical industry include sensors, wireless communication, artificial intelligence, machine learning, and data analytics. Sensors collect data from patients and medical devices, which is then transmitted to healthcare providers through wireless communication. Artificial intelligence and machine learning analyze the data to provide insights

[1] IBM. IBM Watson health announces plans to acquire Truven Health Analytics for $2.6b, extending its leadership in value-based care solutions. 2016. https://www-03.ibm.com/press/us/en/pressrelease/49132.wss.

into patient health, while data analytics identify patterns and trends in patient data to offer actionable insights.

Regarding the innovation efficiency of China's smart medical industry, Hou and Lu (2019) conducted a study using principal component analysis and data envelopment analysis. They found that although the smart medical industry demonstrated good overall growth capacity, its innovation and production efficiency were suboptimal.

In the context of online healthcare, the ERGM method has been utilized by researchers to investigate factors influencing patient interaction networks. Song et al. (2014) explored the factors influencing the formation of patient connections by studying a collaborative friendship network constructed from online healthcare communities using ERGM. This research shed light on the factors influencing informationized medical networks from the patient perspective. Moreover, recent studies have identified several structural dependencies and actor traits that may impact the creation of patient connections in online healthcare communities (Yan et al., 2015). However, there is a scarcity of studies analyzing the formation and influencing factors of joint innovation networks in the smart healthcare industry from the perspective of product developers. Therefore, this paper aims to employ ERGM to construct an innovation network comprising research institutions, universities, hospitals, and other entities, and to examine the factors affecting network formation from the perspectives of network structure and external characteristics.

3. Hypotheses and research methodology

3.1. Hypothesis proposed

Several researchers have determined that three factors contribute to the creation of industrial innovation networks (He et al., 2023). The explanatory variables in ERGM generally include three types: network structure variables, individual attribute variables, and network covariates. Path dependence generated by past connections is the first type. The multidimensional closeness between network nodes is the second type. The third factor is the diversity of innovative subjects.

The first type, network structure variables, contains the endogenous structural effects that are inherent to the internal process of the system of network ties. These variables do not involve actor attributes or other exogenous influences to explain the formation of these local patterns, so it is also called processes of network self-organization (Lusher et al., 2013).

Self-organizing structural dependence is a property of network evolution. Using geometrically weighted edge sharing (Gwesp) can demonstrate this dynamic evolution mechanism of the innovation network. It is a parametric summary measure of the tendency for two nodes in a network to have one or more partners in common when these two actors themselves are directly tied (Caimo and Gollini, 2020).

For both parameters, the weights decrease geometrically as the number of shared partners increases. Consequently, the positive estimated value of the Gwesp parameter shows that the number of shared partners increases in the innovation network and the patent collaborative innovation network to incline more toward the characteristics of the center-edge macro network structure. Given the above, the hypothesis is proposed as follows.

H1. The bigger the value of Gwesp, the greater the likelihood of co-occurrence relationships amongst other nodes.

From the internal perspective, the optimal connection mechanism is an important law affecting the generation of network connections (Ye and Bi, 2020). Under the control of the optimal connection mechanism, nodes with more connections are more likely to make connections with other nodes in the innovation network. Thus, the literature indicates that nodes in a network having an extensive relationship with other nodes may be perceived as trustworthy by others (Osman et al., 2020).

The point degree centrality of the applicants measures the number of co-occurrences with other applicants, facilitating the identification of a node's influence (Tang and Lai, 2019). Applicants with a higher degree of centrality may reflect the heart of industrial innovation, and new cooperative patents may tend to be associated with these applications, indicating a preferred linkage (Hu et al., 2022).

Thus, this paper proposed the following hypotheses:

H2. As the point degree centrality of the applicant node increases, so does the likelihood of co-occurrence relationships with other nodes.

Homophily is used to describe the likelihood of patent partnerships between applicants with similar attributes (Lee et al., 2016). The positive compatibility effect reflects that it is easy to form or maintain patent cooperation between applicants with the same attributes, while the negative compatibility effect reflects that it is not easy to form or maintain patent cooperation between applicants with the same attributes.

From an exogenous perspective, the external characteristics of candidates will also influence the creation of innovation network connections. The time when the applicant participates in the innovation network can reflect some extent the development stage and innovation ability at that time. Applicants who entered the innovation network at the same time tend to have more similar strategic plans. In accordance with Winter et al. (2018), the year in which the node occurs will be considered in this paper.

Two computation methods, Absdiff and Nodecov, are applied to the variable of node emergence time to examine its impact on the establishment of innovation networks. Absdiff reflects the absolute value of the difference of the same attribute value between a pair of nodes, reflecting the impact of the difference of the attribute value between two nodes on the formation or intensity of the relationship. Nodecov represents the sum of the same attribute values of a pair of nodes, reflecting the influence of the attribute value on the formation or intensity change of the relationship between the two nodes. Considering that the smart medical industry is a high-tech emerging industry, and the industrial technology gap between different years is large, the smaller the difference between applicants, the more likely it is to create a link.

Hence, the following hypotheses are put forward:

H3. The lower the Absdiff value of the node's initial appearance year, the greater the likelihood of a co-occurrence association between other nodes

H4. The bigger the Nodecov value of the node's first appearance year, the greater the likelihood that co-occurrence relationships will arise with other nodes

The type of applicants also matters since applicants with diverse organizational systems and profit structures will have vastly different attitudes toward the same knowledge source. Innovation subjects with different attributes, such as enterprise size, age, and ownership, have different behaviors in network formation (Liu et al., 2021a). Cao et al. (2018), after conducting an empirical investigation on the influencing variables of innovation network creation of high-tech businesses in Shanghai, determined that the impact of enterprise ownership on the establishment of innovation networks was insignificant. Since patent cooperation in the smart medical industry requires a large amount of knowledge and information exchange, institutions with the same attributes have more common knowledge reserves, and even easier exchange opportunities between organizations, which is more conducive to the formation of connections. Thus, we make an assumption that:

H5. The larger the value of applicants' properties, the greater the likelihood that other nodes would exhibit co-occurrence relationships.

In addition to the endogenous structure effect and the actor matching effect, other exogenous situational factors also have a particular influence on the formation of the network.

An increasing number of contributions have addressed the relevance of different types of proximity in the transmission of knowledge for innovation network formation, specifically inter-organizational collaborations (Xiao et al., 2023). According to the research of Villani et al. (2017), geographic proximity makes it easier for collaborating organizations to interact and is essential for the establishment of innovative cooperation networks. In the study of Johnston and Huggins (2016), it is confirmed that the geographical distance factor can significantly improve the frequency of innovation network connections between knowledge-intensive enterprises and universities. Geographical proximity can facilitate the formation of innovation networks because, on the one hand, it minimizes the cost of transit and communication between applicants such as businesses, hence promoting the transmission and acquisition of tacit and explicit knowledge. On the other hand, it gives applicants with opportunity for frequent face-to-face communication and helps to increase mutual trust and understanding among applicants (Liu et al., 2021b). In addition, geographic proximity can reduce the risk of information asymmetry and avoid potential conflicts of interest. Hence, we propose the following assumption:

H6. Geographic proximity has a positive effect on innovation network connection.

Cognitive proximity refers to the degree of similarity between the knowledge base and technological background possessed by network participants (Zhang et al., 2020). It generally reflects the cognitive distance between subjects. The majority of scholars use the number of patents owned by each side in different technical sectors as a metric for cognitive proximity (Ji et al., 2022). Innovation subjects will prefer partners with a high degree of cognitive closeness to themselves, and cognitive proximity advantage is frequently simpler to build into a stable and intimate innovation network (Geldes et al., 2015; Chae, 2016). Wu et al. (2016)studied the influencing factors of collaborative innovation between provinces and cities in the Beijing-Tianjin-Hebei region and found that cognitive proximity played a positive role in the development of collaborative innovation.

In the current development period of the smart medical industry, there are many transfers of tacit information between businesses,

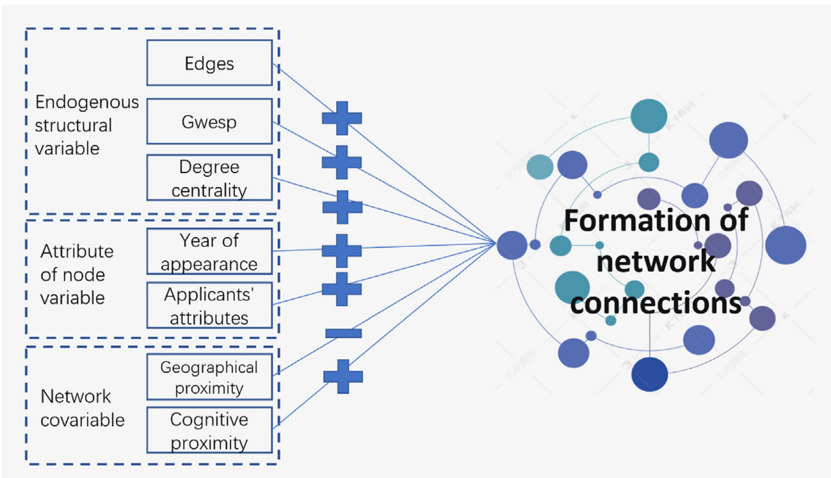

Fig. 2. Schematic diagram of variable relationship.

and most organizations are making exploratory attempts. It is simpler for them to connect with other actors who share the same knowledge base and capabilities (Lata et al., 2018). For these reasons, we assume that:

H7. The larger the cognition proximity, the more similar the applicants' knowledge, and the more favorable it is for the establishment of an innovation network connection.

The relationship between the variables is shown in the Fig. 2

3.2. Data source

Due to the capacity to measure formal relationships between innovation players, patents, academic articles, and collaborative innovation initiatives have been regarded as dependable data sources for quantitative analysis (D Este et al., 2013). Patent data can be classified into several sectors by IPC or CPC number, and it provides a wealth of information on the R&D process and its applications; hence, it is widely utilized in innovation research and research of the digital economy industry (Ouyang et al., 2022). By a specific classification system, patents can be divided into many technological fields. For example, IPC (International Patent Classification) contains a lot of information on R&D processes and applications, so it is widely used in innovation research. In research based on patent data, IPC4 is used widely (Zhang and Qian, 2022). IncoPat patent analysis system was used as a retrieval tool and retrieval data range, and applicant, application date, international classification number, etc., are critical patent information.

For the selection of the main retrieval fields, this paper refers to the research of several scholars in the smart medical field as follows. In the field of intelligent medical industry innovation research, according to different research purposes and data sources, scholars extract different keywords in the smart medical industry. The specific results are shown in the Table 1.

Combined with the methods used by scholars in their articles and the concept of the smart medical industry, five words include “Record Medical”, “Intelligent Health Data”, “Monitor Medical System”, “Wearable Sensor Medical” and “Remote Medical” covered the main functions and equipment of patented products in the smart medical industry are used as the keywords used for retrieval in IncoPat in this paper.

The selected keywords for patent selection in the smart medical field encompass a range of crucial aspects. “Record Medical” refers to methods of recording medical data, such as electronic health record systems, which enhance the accuracy and accessibility of information. “Intelligent Health Data” involves leveraging personal health data through sensors and IoT technologies to provide personalized health guidance. “Monitor Medical System” utilizes sensors and remote monitoring to track patients’ conditions and the status of medical devices in real-time. “Wearable Sensor Medical” focuses on wearable sensors that monitor physiological parameters and offer real-time health guidance. Lastly, “Remote Medical” enables remote medical services by employing communication technologies, thereby improving accessibility and resource allocation. These keywords effectively represent the smart medical industry, encompassing innovative technologies, data analytics, and remote interactions. Their selection for patent searches assists in identifying innovative technologies and solutions within the realm of smart medical.

Patent cooperation raw data only contain names of cooperative enterprises, not their addresses. Thus, the cooperation data are further processed. Also, due to the fact that the addresses of natural persons are not recorded in the patent database, the crawler cannot obtain the patent address information of natural persons. Accordingly, patents involving natural persons were excluded from this study. And only the date of application from January 1, 2005 to October 2022 was used. In order to better fit the research scope set in this paper, independent patents, individual applicants, patent status invalid, non-Chinese mainland enterprises, and duplicate patents were removed through manual screening. After the screening, the number of patent cooperation data items used in the models of this paper is 88, and there are 189 enterprises participated in innovation collaboration.

4. Network construction and analysis

4.1. Network construction

As indicated by Sovacool et al. (2018), pooled cross-section obviates selection bias and induces greater vigor than cross-sectional data analysis. Therefore, the patent data of the smart medical industry in the time course from 2005 to 2022 are used for analysis. The element in the matrix is the existence of co-authors filed by authors. For instance, if a patent includes three co-authors, then one will be assigned to each author (As shown in Table 2).

An undirected weighted matrix is developed based on the nature of the smart medical sector innovation network described in the previous section. The raw data are dichotomized as an adjacency matrix $A = [a_{ij}]$, which represents the patent connection between nodes i and j. This relationship is equal to 1 if it exists and 0 if it does not exist. Since the establishment of innovative partnerships is a

Table 1
Keywords extraction.

Source	Key words in research
Kim et al. (2018)	Health information measurement technology, medical care platform technology, and medical remote service technology
Liu (2018)	Obtaining health indicators, entering them into the system, storing and classifying information, archiving and calculating data
Darwish et al. (2019)	Tracking, identification and authentication, data collection, and sensing sensor devices
Han et al. (2020)	Smart medical et al. 20 keywords

Table 2
Relation of edges in network construction.

type	Identification rules
AB	AB
ABC	AB, AC, BC
ABCD	AB, AC, AD, BD, BC, CD

joint choice of both members, the use of undirected weighted networks is a better representation of existing partnerships. Reflected in the network that ij and ji are the same edges.

The co-occurrence network diagram of the innovation network in China's smart medical industry was generated using NetDraw, a visualization tool integrated within the Ucinet software. The resulting visualization depicting the network is presented in Fig. 3.

4.2. Social network analysis

Social Network Analysis was applied to the constructed networks to investigate their structure. After converting the constructed patent cooperation matrix into an undirected binary network, Ucinet 6.0 is used to analyze the network structure. The result is shown in Table 3.

The density of innovation network can reflect the closeness of patent cooperation among various subjects in the network. Degree centrality represents the number of shortest paths with a distance of 1 to a node. The table shows that the degree centrality of the network is 0.025, and the average degree is 1.365. The table shows that the degree centrality of the network is 0.025, and the average degree is 1.365. That indicates that the innovation network of the smart medical industry in our country is characterized by low density and sparse structure. Network structure features can influence the process of innovation knowledge aggregation (Zhang Chen et al., 2021). Innovation resources in the network have not been fully utilized, and cooperation among innovation entities needs to be further strengthened.

The average path length and average clustering coefficient measure the small-world characteristics of the network. As the result shows, the average distance is 1.221, and clustering coefficient is 0.794. It indicates that each subject passes through 1.2 nodes on average before it can cooperate with another subject. The result of social network analysis China's smart medical industry information innovation network has a “core-edge” pattern with a “small-world network” characteristic. The path length is not the only factor that negatively affects subjects' ability to innovate; a high clustering coefficient in an innovation network is also detrimental to innovation realization (Lin et al., 2010). The network structure for innovation in the smart medical industry is generally not favorable for raising the level of innovation right now.

5. The design of ERGM and hypotheses

The innovation network of China's smart medical industry is complicated. Next, this paper wants to solve the question: What factors can influence and how do they influence the formation of connections within the network of the smart medical industry?

5.1. ERGM construction

Firstly, the hypothesis variables affecting the formation of the smart medical industry's patent cooperation network are proposed. Then the model is built on the basis of Chapter 3. According to the parameter settings in this paper, the equation adopted is shown as follows (Teng et al., 2021).

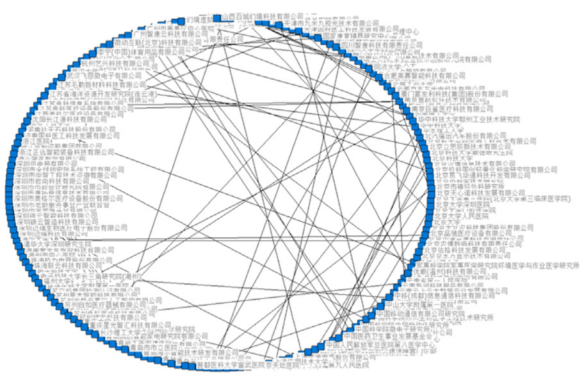

Fig. 3. Innovation network of China's smart medical industry.

Table 3
The result of Social Network Analysis.

Title	Value
Avg Degree	1.365
Core/Periphery fit (correlation)	0.1911
Components	79
Overall graph clustering coefficient	0.794
Weighted Overall graph clustering coefficient	0.673
Avg Distance	1.221
SD Distance	0.443

$$\Pr(Y = y \mid \theta) = \left(\frac{1}{k}\right)\exp\left\{\theta_1^T z1(y,x) + \theta_2^T z2(y,g) + \theta_3^T z3(y)\right\} \quad \text{Equation 1}$$

Where Y = [Y_{ij}] is a 0-1 symmetric matrix. $z_1(y,x)$ and $z_2(y,g)$ respectively represent individual variable and relationship variable. $z_3(y)$ is variable with network structure. θ_1^T, θ_2^T and θ_3^T is the estimation parameter. And k is a constant to ensure that the equation follows the normal probability distribution normalization value. The positive and negative of it represent the influence direction and the value represents the influence degree of the variable on the formation of the network.

This article then evaluates the method with a Monte Carlo simulation. The method of the Markov chain Monte Carlo maximum likelihood estimation (MCMC MLE) is employed to estimate the model (Box-Steffensmeier et al., 2018). With the help of the MCMC MLE, which can compare the random network with the real network and the estimation parameters are continuously optimized until the parameters reach a steady state. The fitting degree of the model can be checked by the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). GOF will be used as another way to verify the validity of the model auxiliarily.

5.2. Variable definition and setting

Both Edge and Gwesp are basic structural variables of the model and can be regressed directly in an R language program without additional computation.

Degree centrality is generated in the application Uci6.

The variable "Year of appearance -Nodecov" and "Year of appearance-Absdiff" are both based on the time nodes first appear in the network. This variable is also easily obtained by combining the IncoPat database and the patent cooperation network.

As for Applicant's attributes, there are five sorts of applicants listed in the IncoPat patent database: people, colleges and universities, businesses, research organizations, and government agencies (medical institutions). This document distinguishes the applicants according to their profit and non-profit qualities, as the hospital's research and development department has non-profit features. Research institutes and for-profit and not-for-profit organizations are classed in one category, while institutions and universities are classified in another. If the attribute between two nodes is the same, it is counted as 1; if it is different, it is 0. Thus, a positive definite symmetric network of the same size as the patent cooperation network is constructed.

In this paper, a matrix is used to represent the geographical proximity between innovation subjects. A geographical distance matrix is produced based on the geographic location of the joint application in IncoPat. After crawling the longitude and latitude coordinates of 679 cities in China with Python on the website (http://citycode.blacklife.cn/index.php), this paper calculated the geographical distance between cities. The actual distance between the two sides of technology transfer is calculated according to the longitude and latitude of the city where the enterprise is located. With reference to the research of Zhao et al. (2016) the calculation formula is as follows:

$$D_{ij} = C\left\{\arccos\ \left[\sin(lat_i)\sin\left(lat_j\right) + \cos(lat_i)\cos\left(lat_j\right)\cos\ \left(\left|log_i - log_j\right|\right]\right\}$$

Table 4
Specification of variables.

Type of parameter	Variables	Operationalization
Endogenous structural variable	Edges	The number of edges in the network
Endogenous structural variable	Gwesp	The number of triangular structures in the network
Endogenous structural variable	Degree centrality	Point degree of a node in the network center degree
Attribute of node variable	Year of appearance -Nodecov	The year in which the node first appeared in the network
Attribute of node variable	Year of appearance-Absdiff	The year in which the node first appeared in the network
Attribute of node variable	Applicant's attributes-Nodematch	Ownership property of a node (colleges and medical institution are represented by 1, enterprise and research institutes, are represented by 2)
Network covariable	Geographical proximity	Geospatial distance network between nodes
Network covariable	Cognitive proximity	IPC4 matching network between nodes

Latitude (lat) and longitude (long) are measured in radians. C = 3437, which is the coefficient that converts radians into miles on the Earth's surface.

The IPC number of a patent, also known as the International Patent Classification Number, is a symbolic hierarchy system that classifies the patent according to the different technical fields it belongs to and can reveal its basic technology and function (Dereli et al., 2011).

Given the availability of data, this paper uses the top four IPC patent numbers (IPC4 for short) applied by patent applicants when they first appear in the smart medical industry innovation network to replace the cognitive attributes of enterprises. If an enterprise belongs to the same cognitive type, it is assigned a value of 1; otherwise, it is assigned a value of 0.

The variable settings in this paper are shown in Table 4.

Considering that the endogenous structure variable of the network has only one value, and the formats of geographical distance and cognitive distance are both network variables, only the descriptive statistical results of node variables are shown here (see Table 5).

6. Regression analysis and empirical results

Following Duxbury and Wertsching (2023), this paper uses the statnet, ergm, and texreg package of R language to estimate and calculate the parameters of the ERGM which set in Chapter 4. The package allows users to obtain approximate Maximum Likelihood Estimates (MLEs) and simulate random networks from a specified ERGM (Capone and Lazzeretti, 2018). Five models are established separately, and endogenous structural variables, node attribute variables, and network covariates are successively added as explanatory variables.

6.1. *Empirical results*

The empirical results are presented in the table below.

The exponential random graph model (ERGM) captures the propensity of relationship formation within the network through the edges term. The regression estimation results, as shown in Table 6, highlight several significant findings. In Model (1) and Model (2), which focus on the endogenous structural variables of the network, the variable representing the number of edges exhibits a significant negative effect at the 0.01% level, indicating a relatively low density of the innovation network in the smart medical industry. Furthermore, the estimation results from Model (1) indicate that Gwesp exhibits a significantly positive effect at the 0.01% level, with an estimated coefficient of 1.595. This finding suggests that the occurrence probability of triangular closed structures is high in the innovation network of the smart medical industry. Such structures contribute to the development trajectory of the industry's value chain. These results underscore the intricate nature of innovation diffusion processes and emphasize the importance of adopting a network perspective. It becomes evident that not only direct links between two entities are essential for diffusion, but also indirect connections within the entire network play a crucial role.

Model (2) extends the analysis of model (1) by incorporating additional endogenous network variables. The results of Model (2) demonstrate that the Nodecov variable, representing the year of the node's earliest appearance, exhibits a negative effect at a significance level of 0.1%. This suggests that the closer the appearance years of different applicants are, the less likely they are to form network connections. Similarly, the Absdiff variable, measuring the gap in node appearance years, also displays a negative effect at a significance level of 0.01%. This finding implies that whether the time gap between applications is large or small, it presents obstacles to innovation cooperation between enterprises or organizations in various ways (Sun and Peng, 2021). Consequently, the possibility of cross-year innovation cooperation between different enterprises is minimal. This outcome highlights the imperfect nature of innovation networks within the smart medical industry and the significant resistance to cross-year cooperation. Additionally, the Nodematch variable, capturing the proximity of node attributes, demonstrates a positive but statistically insignificant effect. This suggests that a closer alignment of attributes between different applicants promotes the formation of network connections.

Model (3) extends the analysis of Model (2) by introducing variables related to homogamy and heterogeneity of applicant attributes. The results reveal a distinctly positive and statistically significant effect of point degree centrality of the applicant at the 0.1% level. When all other node elements are held constant, applicants with higher point degree centrality are more likely to establish co-occurrence relationships with other applicants. This finding confirms the influential role of the universal optimal connection mechanism in the formation of innovation networks within the smart medical industry, in line with previous research on complex networks (Barabasi, 2009).

Model (4) introduced covariables of the geographic proximity network. The distance network is significantly negative at the 0.1% level. This demonstrates that there is a clear overlap between the geographical network of the applicant and the innovation network of the smart medical industry, which has a significant positive impact on the latter network. Specifically, shorter geographic distances between applicants are associated with a higher likelihood of generating innovative connections and promoting the development of the

Table 5
Descriptive statistics of variables.

Variables	N	Mean	Std	Min	Max
Degree centrality	172	1.42	0.79	1	7
Year of appearance	172	2020.08	0.77	2019	2021
Applicaint's attributes	172	1.69	0.86	1	3

Table 6
Empirical results.

	Model (0)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Edges	-4.91794***	-5.3932***	-0.39844	-0.94053*	2.36393***	1.63834**
	(0.08836)	(0.1132)	(0.44125)	(0.43145)	(0.59309)	(0.62891)
Gwesp		1.5950***	1.05872***	0.93341***	0.55270***	0.41815**
		(0.1377)	(0.1361)	(0.14042)	(0.14551)	(0.14455)
Year of appearance -Nodecov			-0.10853***	-0.11938***	-0.11648***	-0.11861***
			(0.01339)	(0.01355)	(0.01639)	(0.01858)
Year of appearance-Absdiff			-1.67489***	-1.718748***	-1.76245***	-1.66871***
			(0.15715)	(0.160365)	(0.16987)	(0.17592)
Applicaint's attributes-Nodematch			0.04568	0.03012	0.02853	-0.13270
			(0.17657)	(0.179065)	(0.19827)	(0.21236)
Degree centrality				0.28577***	0.36880***	0.38184***
				(0.04297)	(0.05084)	(0.05775)
Geographical proximity					-0.63043***	-0.65243***
					(0.05060)	(0.05268)
Cognitive proximity						2.07459***
						(0.22942)
AIC	1530	1432	1102	1064	944.4	775.5
BIC	1538	1448	1141	1110	998.9	837.7

innovation network.

Lastly, Model (5) demonstrates a significant positive effect of the IPC network covariate coefficient at the 0.1% level. This coefficient represents the level of cognitive closeness among applicants. The findings indicate that innovation network connections are more likely to form when applicant enterprises exhibit greater similarity in technology and knowledge structures, as discussed in the previous chapter.

6.2. Goodness-of-fit analysis

Currently, the most commonly employed strategy to evaluate the goodness of fit of the ERGM model is through the utilization of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) included in the regression results table. Smaller values of

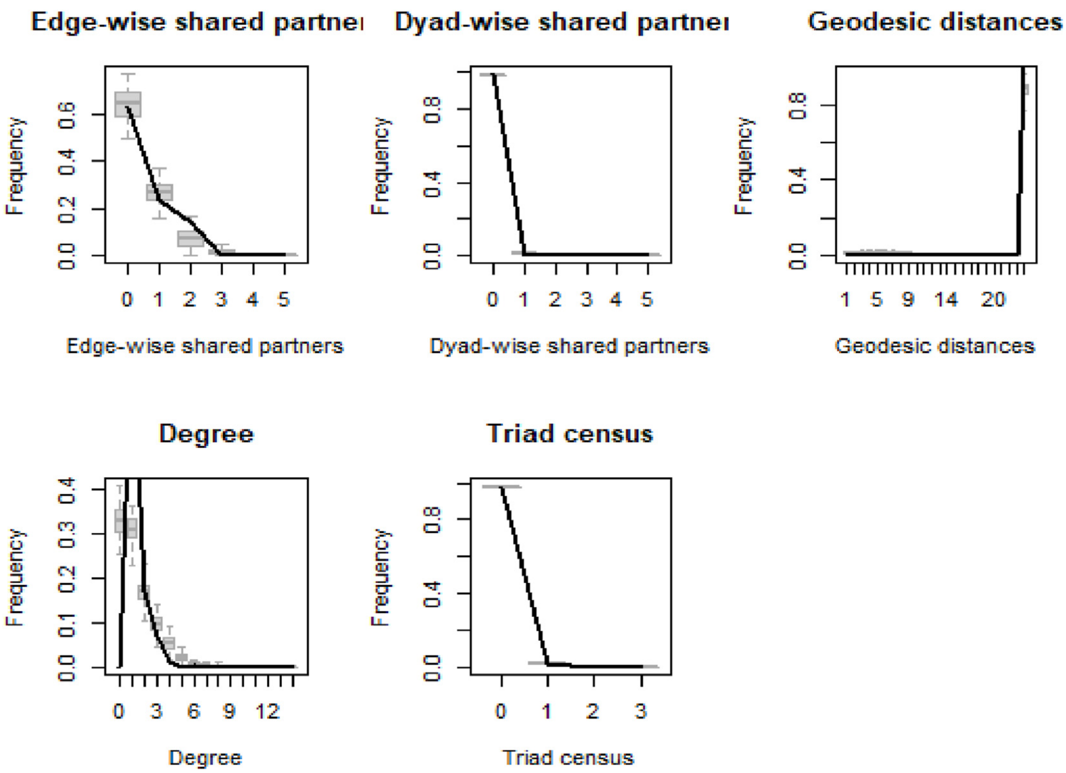

Fig. 4. The result of Goodness of fit.

AIC and BIC indicate better model fit.

In general, Model (5) incorporates all variables, and when compared to the previous estimation results, it exhibits the lowest AIC and BIC values, indicating the highest goodness of fit for the model. The variable estimation results from Models (1) to (5) consistently display the same sign, and the AIC and BIC values progressively decrease. This verifies, to a certain extent, the robustness of the model. By employing the AIC and BIC as evaluation criteria, this study provides empirical evidence supporting the goodness of fit of the ERGM model. The consistent sign of the variable estimation results across models further enhances the reliability and validity of the findings (see Fig. 4).

The goodness of fit (GOF) is another meaningful way to examine the fitness of the model, and it helps to reproduce important properties in observed networks (Duarte-Barahona et al., 2020). The solid black line represents the statistical characteristics of the observed network, and the boxplot represents the statistical characteristics of the simulated network; since the median of the boxplot is close to the solid black line of the observed network, it indicates that the GOF of Model (5) is good.

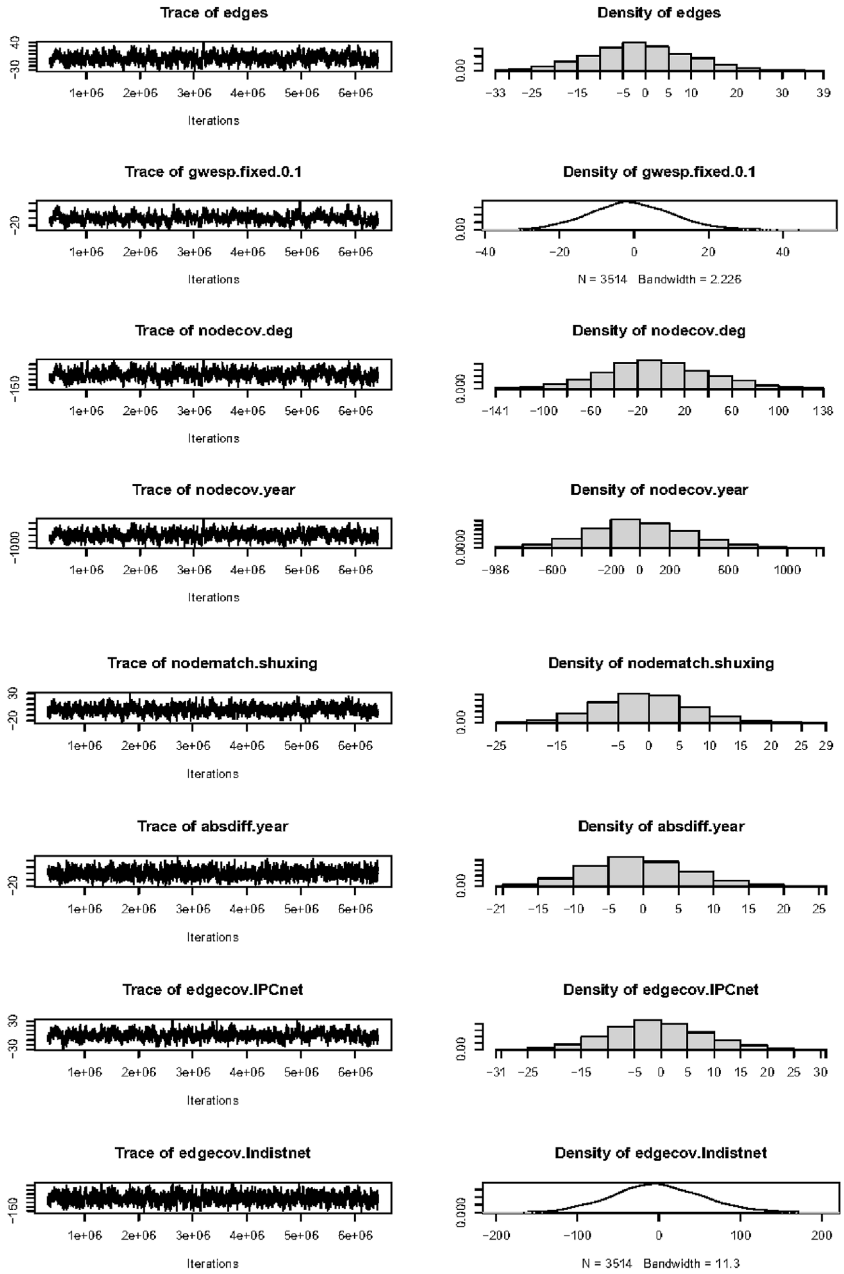

Fig. 5. The result of MCMC test.

6.3. Robustness test

In addition to using the above methods to detect the goodness of fit of the model, model diagnosis can also assist in determining whether the estimation algorithm has converged or has the problem of approximate degradation. Through the MCMC parameter estimation algorithm, Fig. 5 can be obtained.

This image shows the state of the model at its final iteration. The plot on the left takes each statistical term in the model as a unit and uses the MCMC chain to make a time series to show the change of variables, while the plot on the right shows the histogram of the corresponding MCMC chain. A good simulation needs to avoid a long flat region and a continuous development trend in one direction. Besides, all variables need to converge to the horizontal line (Levin and Peres, 2019). Thus the results are well configured and the model has good convergence.

7. Conclusion and discussion

This paper aimed to investigate the different roles of factors, including the attribute and distance of participants in smart medical innovation network formations. In this paper, the data of patent cooperation applications among innovation subjects such as enterprises, medical institutions, universities, and scientific research institutions on IncoPat was used to build the intelligent medical industry innovation network. Further, the exponential random graph model (ERGM) was employed to investigate the creation mechanism of the industrial innovation network and to quantify the degree and impact of influencing factors. Based on the findings, the following conclusions can be drawn:

Firstly, the study reveals that the innovation network of the smart medical sector is in its early stages of development. The core edge structure, small-world network characteristics, and low network density and centrality all pose certain hindrances to the level of innovation within the smart medical industry.

Secondly, the chain development path of the triangular structure in the network leads the patent collaborative innovation network to be more inclined to the characteristics of the center-edge macro network structure. This result is a powerful proof of innovative path dependence, which occurs when a subject's innovation process followed a path shaped and constrained by its innovation approach (Thrane et al., 2010). Furthermore, central nodes in the network are more likely to establish new innovative and collaborative relationships. These findings, from a network perspective, suggest the existence of increasing centrality in already-central locations and the presence of preferential attachment mechanisms, as observed in related studies (Sun and Grimes, 2017). The rationale behind this conclusion may be related to the conclusion of Hu et al. (2012), who identified key patents at the network center as drivers of integrating different technological trajectories to enhance network efficiency.

Moreover, the emergence of new connections in the network predominantly occurs between applicants from the same year or relatively recent years. This suggests that in the realm of innovative collaboration within the smart medical industry, participants are more likely to connect with new counterparts. It also indicates that new subjects tend to establish connections and that collaborative cooperation spanning different time periods has not yet fully formed within the network. The significance of relationships between subjects of different natures is relatively weak, suggesting that medical institutions, universities, and enterprises, such as equipment manufacturers, in China primarily engage in transactional relationships with limited involvement in cooperative product development and innovation processes, as observed by Zhang and Rao (2021b).

In order to enhance the innovation network within the smart medical industry, it is crucial for the government and market stakeholders to provide greater opportunities for cooperation and innovation to peripheral enterprises. This approach helps prevent an excessive concentration of resources in the dominant players of the industry.

Thirdly, it is observed that geographical distance remains a significant factor impeding innovation cooperation among enterprises. This phenomenon can be attributed to the tacit nature of the knowledge involved, as the technologies employed in the medical industry are often highly intricate (Lin and Wang, 2019). Consistent with this result, the strong interconnection of regional technology development and regional demand becomes evident (Losacker and Liefner, 2020).

Apart from that, cognitive distance is also a key factor affecting network construction, and the same knowledge structure helps enterprises to cooperate as Cao et al. (2021) who believe the success of collaboration networks depends on some basic commonalities such as common goals, common or interoperable medical infrastructures among their members studied. However, we should notice the importance of remote technological fields because it helps generate new knowledge and radical innovations and avoid cognitive lock-in (Dong et al., 2020).

This phenomenon can also promote the iterative evolution of knowledge and innovation to a certain extent, but it will also lead to difficulties in cross-professional cooperation, which is not conducive to the cross-field dissemination of knowledge and affects the diversified development of innovation (Rosenthal et al., 2010). If emerging technology tools such as the internet and cloud computing can be used to solve the distance limitation and access new advanced knowledge and information using online technology and open international innovation (Kapetaniou and Lee, 2019).

In conclusion, the innovation network of China's smart medical industry still contains enterprises with limited innovation capabilities and insufficient joint innovations among diverse themes.

8. Implications and limitations

8.1. Theoretical and practical implications

This study makes several contributions to the field of innovation networking in the smart medical industry. The logical organization of the key contributions is as follows:

Firstly, this study combines internal and external factors of the network to examine the factors and mechanisms that influence the innovation network. By utilizing the advantages of the ERGM model, the study expands on internal structural factors of networks, enriching the theoretical foundation of innovation networks. Based on the frameworks established by economic geographers, such as Zhou et al. (2021), this study selects network structure variables, individual attribute variables, and network covariates as three dimensions to examine the influence mechanism.

Furthermore, it contributes to the existing literature by introducing different factors from previous research, such as the time when a node first participates in the network，and measuring their effects on innovation networks. In contrast to existing studies on network influences, such as the empirical study by Ma et al. (2020)), which identified the inverted U-shaped influence of structural holes and network prominence on network structure, this study offers a fresh perspective on network evolution.

Moreover, this study identifies key influencing factors in the field of innovation networking in the smart medical industry. It further validates the applicability and accuracy of innovation network theory. At the network structure level, the study confirms the presence of innovative path dependence and preferential attachment mechanisms during the formation of network connections. At the node attribute level, the initial year of institutional participation is identified as a critical factor influencing network relationships. Additionally, at the network covariate level, closer geographical distances and similar cognitive structures significantly impact the formation of network connections.

The findings of this study have implications beyond the Chinese smart medical industry. They demonstrate some degree of similarity when applied to networks constructed with different types of data, such as urban trade networks, particularly in the context of innovation collaboration networks. Therefore, this research provides valuable insights into variable selection and unique mechanisms, enriching both the methodological and substantive aspects of empirical research on the influencing factors of innovation networks.

Lastly, this study reveals the influences and mechanisms behind the formation of innovation networks in the smart medical industry through the analysis of ERGM model results. It enhances the understanding of the changing patterns, willingness, and mechanisms of collaboration among different organizations within the smart medical industry. Consequently, it offers important theoretical guidance on influential factors and directions for studying the evolution of innovation networks.

In addition, this paper also makes some important theoretical contributions at the level of digital economy. The digital economy has become a key role in promoting the high-quality and rapid development of contemporary China's economy. There are also a considerable proportion of articles studying the development of the digital economy that mention industrial trade networks. However, many studies related to the digital economy focus on the perspective of cities, and the data used are more from the economic activities related to enterprises (Chen and Zhu, 2022). The data this paper innovatively uses are from enterprises, scientific research institutions, hospitals, and other subjects of various natures. The findings of this study support the development of an innovation-driven digital economy, supplementing the static descriptive studies of digital economy development in related fields (Pan et al., 2022), and providing a profound dynamic analysis of the evolutionary mechanisms of digital economy industry networks.

The formation and operation of the smart medical industry rely on a vast amount of digital data, which can originate from medical devices, sensors, electronic health records, and other sources. Consequently, the smart medical industry is capable of providing more precise and personalized healthcare services, thus driving the data-driven development of the digital economy. Meanwhile, this paper constructs an innovation network from an industry perspective, which refines the empirical research on the development of the digital economy.

From the perspective of the industry, In recent years, more and more Chinese scholars have tried to analyze the influencing factors and mechanisms from the perspective of social networks among patients in internet medical treatment (Fu et al., 2021). However, few previous studies assess the influence of innovation networks from the point of view of patent applicants. This paper fills up the shortage of innovation network analysis at the production end, finds out the important influencing factors represented by geographical distance and cognitive distance, and confirms the influencing mechanism, which is conducive to the further development of the industry. The study identifies important influencing factors, represented by geographical distance and cognitive distance, and confirms the influencing mechanism. This analysis contributes to the further development of the industry by shedding light on the factors and mechanisms that affect innovation networks at the production end.

Furthermore, this study holds practical implications for the smart medical industry in China. Collaborative networks for medical services are relatively rare in the country (Lai et al., 2012). By conducting empirical research, this paper examines the main factors influencing the innovation network in the smart medical industry and analyzes the existing structural problems within the network. Consequently, it provides valuable theoretical insights and guidance for the industry's development.

The research findings reveal a significant industry divide in terms of collaborative research and development capabilities among institutions in China's smart medical industry. The presence of different knowledge structures and organizational frameworks hinders the formation of innovation collaborations. However, given the nature of the smart medical industry, which necessitates the integration of innovation from related industries within the digital economy, it becomes increasingly urgent to achieve collaborative creation and promote the optimization and upgrading of industry structure. Overall, this study contributes to improving the efficiency of innovation operations and expanding the scale of industrial innovation within the smart medical industry. Furthermore, it highlights the profound impact of innovation in the medical technology industry on societal well-being.

8.2. Limitations and further research

To enable a concise description of the local selection forces which control the structure of a network, up to now, ERGM has been a popular tool to quantify the strength of the intra-group effect in the field of economics and other subject. However, the binary network used in traditional ERGM method is converted from the multi-valued matrix, so the problem of information loss appears in the process of transformation. The results of this paper show that enterprises and organizations tend to generate innovative connections with geographical locations, cognitive structures, and nodes that are close in time in the network. But the model can't explain to what extent these factors affect innovative connection intensity. Thus, the valued ERGM proposed by Krivitsky (2012)\ can explain not only the appearance of network connections but also the strength of network connections.

Declaration of competing interest

The author Chao Lu is an Associate Editor for [Journal of Digital Economy] and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research is supported by National Natural Science Foundation of China (Grant No. 72174116), and The Science Research Projects of Yibin Sanjiang New Area (Grant No. 2023SJXQRKX001).

References

Ahrweiler, P., Keane, M.T., 2013. Innovation networks. Mind Soc. 12 (1), 73–90.
Balland, P., Belso-Martínez, J.A., Morrison, A., 2016. The dynamics of technical and business knowledge networks in industrial clusters: embeddedness, status, or proximity? Econ. Geogr. 92 (1), 35–60.
Barabasi, A., 2009. Scale-free networks: a decade and beyond. Science 325, 412–413.
Bathelt, H., Buchholz, M., 2019. Outward foreign direct investments as a catalyst of urban-regional income development? Evidence from the United States. Econ. Geogr. 95 (5), 442–466.
Bessant, J., Alexander, A., D W, 2017. Responsible innovation in healthcare-the case of health information tv. Int. J. Innovat. Manag. 21 (8), 1740012.
Block, P., Stadtfeld, C., Snijders, T.A.B., 2016. Forms of dependence: comparing SAOMs and ERGMs from basic principles. Socio. Methods Res. 48 (1), 202–239.
Box-Steffensmeier, J.M., Christenson, D.P., Morgan, J.W., 2018. Modeling unobserved heterogeneity in social networks with the frailty exponential random graph model. Polit. Anal. 26 (1), 3–19.
Brennecke, J., Rank, O., 2017. The firm's knowledge network and the transfer of advice among corporate inventors-A multilevel network study. Res. Pol. 46 (4), 768–783.
Broekel, T., Hartog, M., 2013. Explaining the structure of inter-organizational networks using exponential random graph models. Ind. Innovat. 20 (3), 277–295.
Bukht, R., Heeks, R., 2018. Defining, conceptualising and measuring the digital economy. Int. Organ. Res. J. 13, 143–172.
C F, 1991. Networks of innovators a synthesis of research issues. Res. Pol. 5 (20), 499–514.
Caimo, A., Gollini, I., 2020. A multilayer exponential random graph modelling approach for weighted networks. Comput. Stat. Data Anal. 142, 106825.
Cao, X., Zeng, G., Zhu, Y., 2018. Influencing factors of shanghai high-tech industry innovation networking. Sci. Geogr. Sin. 8 (38), 1301–1309.
Cao, Y., Li, G., Mao, J., et al., 2019. An empirical study on knowledge connection mechanism of interdisciplinary field based on ERGM. Library and Information Service 19 (63), 128–135.
Cao, X., Zeng, G., Lin, L., et al., 2021. Hierarchical characteristics and proximity mechanism of intercity innovation networks: a case of 290 cities in China. Complexity, 5538872.
Cao, X., Teng, T., Zeng, G., et al., 2022. The influencing factors of industry innovation networking: evidence from Shanghai's high-tech industry. Int. J. Technol. Manag. 89, 187.
Capone, F., Lazzeretti, L., 2018. The different roles of proximity in multiple informal network relationships: evidence from the cluster of high technology applied to cultural goods in Tuscany. Ind. Innovat. 25 (9), 897–917.
Chae, S.W., 2016. Perceived proximity and trust network on creative performance in virtual collaboration environment. Procedia Comput. Sci. 91, 807–812.
Chen, B., Zhu, H., 2022. Has the digital economy changed the urban network structure in China?-Based on the analysis of China's top 500 new economy enterprises in 2020. Sustainability 14 (1), 150.
Cranmer, S.J., Desmarais, B.A., 2011. Inferential network analysis with exponential random graph models. Polit. Anal. 19 (1), 66–86.
D Este, P., Guy, F., Iammarino, S., 2013. Shaping the formation of university-industry research collaborations: what type of proximity does really matter? J. Econ. Geogr. 13, 537–558.
Darwish, A., Hassanien, A.E., Elhoseny, M., et al., 2019. The impact of the hybrid platform of internet of things and cloud computing on healthcare systems: opportunities, challenges, and open problems. J. Ambient Intell. Hum. Comput. 10 (10), 4151–4166.
Dereli, T., Baykasoğlu, A., Durmuşoğlu, A., et al., 2011. Enhancing technology clustering through heuristics by using patent counts. Expert Syst. Appl. 38 (12), 15383–15391.
Desmarchelier, B., Djellal, F., Gallouj, F., 2020. Towards a servitization of innovation networks: a mapping. Publ. Manag. Rev. 22 (9), 1368–1397.
Dong, X., Zheng, S., Kahn, M.E., 2020. The role of transportation speed in facilitating high skilled teamwork across cities. J. Urban Econ. 115, 103212.
Duarte-Barahona, R., Arceo-May, E., Huerta-Quintanilla, R., 2020. Friendship Formation in the classroom among elementary school students: complex networks and their applications. In: 8th International Conference on Complex Networks and Their Applications (Complex Networks), vol. 882, pp. 403–414.
Duxbury, S.W., Wertsching, J., 2023. Scaling bias in pooled exponential random graph models. Soc. Network. 74, 19–30.
Fan, F., Dai, S., Zhang, K., et al., 2021. Innovation agglomeration and urban hierarchy: evidence from Chinese cities. Appl. Econ. 53 (54), 6300–6318.
Fu, Y., Tang, T., Long, J., et al., 2021. Factors associated with using the internet for medical information based on the doctor-patient trust model: a cross-sectional study. BMC Health Serv. Res. 21 (1), 1268.
Geldes, C., Felzensztein, C., Turkina, E., et al., 2015. How does proximity affect interfirm marketing cooperation? A study of an agribusiness cluster. J. Bus. Res. 68 (2), 263–272.
Gui, Q., Liu, C., Du, D., 2019. Globalization of science and international scientific collaboration: a network perspective. Geoforum 105, 1–12.
H. D, 2013. A smart healthcare systems framework. IT Professional 15 (5), 38–45.
Han, J., Hyun, Y., Chae, U., et al., 2020. A study on the healthcare technology trends through patent data analysis. Journal of Digital Convergence 18 (3), 179–187.

Hazir, C.S., Autant-Bernard, C., 2014. Determinants of cross-regional R&D collaboration: some empirical evidence from Europe in biotechnology. Ann. Reg. Sci. 53 (2), 369–393.
He, X., Dong, Y., Wu, Y., et al., 2019. Factors affecting evolution of the interprovincial technology patent trade networks in China based on exponential random graph models. Physica A 514, 443–457.
He, C., Liu, F., Dong, K., et al., 2023. Research on the formation mechanism of research leadership relations: an exponential random graph model analysis approach. Journal of Informetrics 17 (2), 101401.
Hermans, F., 2021. The contribution of statistical network models to the study of clusters and their evolution. Pap. Reg. Sci. 100 (2), 379–403.
Hou, X., Lu, P., 2019. Competitiveness of frontier emerging industry based on data envelopment analysis. Sci. Technol. Eng. 24 (19), 248–253.
Hu, X., Rousseau, R., Chen, J., 2012. A new approach for measuring the value of patents based on structural indicators for ego patent citation networks. J. Am. Soc. Inf. Sci. Technol. 63 (9), 1834–1842.
Hu, Z.B., Wu, G.D., Wu, H.Y., et al., 2022. Cross-sectoral preparedness and mitigation for networked typhoon disasters with cascading effects. Urban Clim. 42 (1), 101140.
Ji, Y., Yu, X., Sun, M., et al., 2022. Exploring the evolution and determinants of open innovation: a perspective from patent citations. Sustainability 14 (3), 1618.
Jiao, C., Wang, T., Liu, J., et al., 2017. Using exponential random graph models to analyze the character of peer relationship networks and their effects on the subjective well-being of adolescents. Front. Psychol. (8), 583.
Johnston, A., Huggins, R., 2016. Drivers of university-industry links: the case of knowledge-intensive business service firms in rural locations. Reg. Stud. 50 (8), 1330–1345.
Kapetaniou, C., Lee, S.H., 2019. Geographical proximity and open innovation of SMEs in Cyprus. Small Bus. Econ. 52 (1), 261–276.
Kaplan, S., Tripsas, M., 2008. Thinking about technology: applying a cognitive lens to technical change. Res. Pol. 37 (5), 790–805.
Kim, D., Cho, S.H., Lee, J., et al., 2018. A study on the competitive analysis of digital healthcare in korea through patent analysis. Journal of Digital Convergence 16 (9), 229–237.
Krivitsky, P.N., 2012. Exponential-family random graph models for valued networks. Electronic Journal of Statistics 6, 1100–1128.
Lai, I.K.W., Tam, S.K.T., Chan, M.F.S., 2012. Knowledge cloud system for network collaboration: a case study in medical service industry in China. Expert Syst. Appl. 39 (15), 12205–12212.
Lata, R., von Proff, S., Brenner, T., 2018. The influence of distance types on co-patenting and co-publishing in the USA and Europe over time. Ann. Reg. Sci. 61 (1), 49–71.
Laursen, K., Masciarelli, F., Prencipe, A., 2012. Regions matter: how localized social capital affects innovation and external knowledge acquisition. Organ. Sci. 23 (1), 177–193.
Lee, S.K., Kim, H., Piercy, C.W., 2016. The role of status differentials and homophily in the formation of social support networks of a voluntary organization. Commun. Res. 46 (2), 208–235.
Levin, David A., Peres, Yuval, 2019. Markov Chains and Mixing Times, second ed. American Mathematical Society, Providence.
Li, M., Zhang, M., Oteng Agyeman, F., et al., 2021. Research on the influence of industry-university-research cooperation innovation network characteristics on subject innovation performance. Math. Probl Eng., 4771113
Liang, Z., Chen, J., Jiang, D., et al., 2022. Assessment of the spatial association network of green innovation: role of energy resources in green recovery. Resour. Pol. 79, 103072.
Lin, L., Wang, F., 2019. Geographical proximity vs network tie: innovation of equipment manufacturing firms in shanghai, China. Erdkunde 73 (3), 185–198.
Lin, L., Zheng, X., Ge, J., 2010. Study on the knowledge transfer in the university-industry cooperation based on the small-world network. Sci. Technol. Prog. Policy 3 (27), 5–8.
Liu, S., 2018. Analysis of the new health management based on health internet of things and cloud computing. AIP Conf. Proc. 1967 (1), 40034.
Liu, Z., Lyu, J., 2020. Measuring the innovation efficiency of the Chinese pharmaceutical industry based on a dynamic network DEA model. Appl. Econ. Lett. 27 (1), 35–40.
Liu, W., Yang, J., 2018. The evolutionary game analysis and simulation with system dynamics of manufacturer's emissions abatement behavior under cap-and-trade regulation. Sustainability 12 (10), 4585.
Liu, K., Che, Q., Wang, C., et al., 2021a. The connection, scale and formation mechanism of emerging industry innovation network. Studies in Science of Science 4 (39), 622–631.
Liu, J., Chong, Z., Lu, S., et al., 2021b. The evolution and determinants of interorganizational coinvention networks in new energy vehicles: evidence from shenzhen, China. Complexity (3), 1–12.
Losacker, S., Liefner, I., 2020. Regional lead markets for environmental innovation. Environ. Innov. Soc. Transit. 37, 120–139.
Lundvall, B., 2007. National innovation systems-analytical concept and development tool. Ind. Innovat. 14, 95–119.
Lusher, D., Koskinen, J., Robins, G., 2013. Exponential Random Graph Models for Social Networks: Theory, Methods and Applications. Cambridge University Press, Cambridge.
Ma, D., Zhang, Y., Zhang, F., 2020. The influence of network positions on exploratory innovation: an empirical evidence from China's patent analysis. Sci. Technol. Soc. 25 (1), 184–207.
Maggioni, M.A., Uberti, T.E., 2011. Networks and geography in the economics of knowledge flows. Qual. Quantity 45 (5), 1031–1051.
Monteith, S., Glenn, T., 2016. Automated decision-making and big data: concerns for people with mental illness. Curr. Psychiatr. Rep. 18 (12), 1–12.
Muller, E., Peres, R., 2019. The effect of social networks structure on innovation performance: a review and directions for research. Int. J. Res. Market. 36 (1), 3–19.
Onodera, R., Sengoku, S., 2018. Innovation process of mHealth: an overview of FDA-approved mobile medical applications. Int. J. Med. Inf. 118, 65–71.
Osman, L.H., Othman, A.S., Palil, M.R., 2020. Does being central in formal network improve trust projection? A socail network analysis of supply network structure. Logforum 16 (1), 85–102.
Ouyang, X., Sun, Z., Xu, X., 2022. Patent system in the digital era-Opportunities and new challenges. Journal of Digital Economy 1 (3), 166–179.
Pan, X., Ming, Y., Li, M., et al., 2020. Inter-regional innovation correlation effects and influencing factors in China. Bus. Process Manag. J. 4 (26), 925–941.
Pan, W., Xie, T., Wang, Z., et al., 2022. Digital economy: an innovation driver for total factor productivity. J. Bus. Res. 139, 303–311.
Powell, W.W., White, D.R., Koput, K.W., et al., 2005. Network dynamics and field evolution: the growth of interorganizational collaboration in the life sciences. Am. J. Sociol. 110 (4), 1132–1205.
Qin, Y., Gang, Z., 2014. Research progress in innovation network: a perspective from economic geography. Hum. Geogr. 3 (34), 7–13.
Ren, X., Li, J., Shi, Y., 2022. Can digital economic attention spillover to financial markets? Evidence from the time-varying Granger test. Journal of Digital Economy 1 (2), 102–116.
Rosenthal, A., Mork, P., Li, M.H., et al., 2010. Cloud computing: a new business paradigm for biomedical information sharing. J. Biomed. Inf. 43 (2), 342–353.
Schiavone, F., Mancini, D., Leone, D., et al., 2021. Digital business models and ridesharing for value co-creation in healthcare: a multi-stakeholder ecosystem analysis. Technol. Forecast. Soc. Change 166, 120647.
Schierjott, I., Brennecke, J., Rank, O.N., 2018. Entrepreneurial attitudes as drivers of managers' boundary - spanning knowledge ties in the context of high-tech clusters. J. Small Bus. Manag. 56 (1), 108–131.
Shi, Y., Gao, Y., Luo, Y., et al., 2022. Fusions of industrialisation and digitalisation (FID) in the digital economy: industrial system digitalisation, digital technology industrialisation, and beyond. Journal of Digital Economy 1 (1), 73–88.
Snijders, T., 2001. The statistical evaluation of social network dynamics. Socio. Methodol. 31, 361–395.
Song, X., Jiang, S., Yan, X., et al., 2014. Collaborative Friendship Networks in Online Healthcare Communities: an Exponential Random Graph Model Analysis. Springer International Publishing, Cham.
Sovacool, B.K., Axsen, J., Sorrell, S., 2018. Promoting novelty, rigor, and style in energy social science: towards codes of practice for appropriate methods and research design. Energy Res. Social Sci. 45, 12–42.

Sun, Y., Grimes, S., 2017. The actors and relations in evolving networks: the determinants of inter-regional technology transaction in China. Technol. Forecast. Soc. Change 125, 125–136.
Sun, Y., Peng, S., 2021. Development mechanism of cohesive subgroups' urban innovation networks in the yangtze river delta: based on the valued ERGM. Econ. Geogr. 9 (41), 22–30.
Tang, P., Lai, S., 2019. A framework for managing public security risks with complex interactions in cities and its application evidenced from Shenzhen City in China. Cities 95, 102390.
Teng, T., Cao, X., Chen, H., 2021. The dynamics of inter-firm innovation networks: the case of the photovoltaic industry in China. Energy Strategy Rev. 33, 100593.
Thrane, S., Blaabjerg, S., Møller, R.H., 2010. Innovative path dependence: making sense of product and service innovation in path dependent innovation processes. Res. Pol. 39 (7), 932–944.
Villani, E., Rasmussen, E., Grimaldi, R., 2017. How intermediary organizations facilitate university-industry technology transfer: a proximity approach. Technol. Forecast. Soc. Change 114, 86–102.
Vinciguerra, S., Frenken, K., Valente, M., 2010. The geography of internet infrastructure: an evolutionary simulation approach based on preferential attachment. Urban Stud. 47 (9), 1969–1984.
Wang, X., Dong, B., Jiang, Y., 2021a. Smart medical prediction for guidance: a mechanism study of machine learning. Journal of Healthcare Engineering, 2474473.
Wang, M., Lin, H., Huang, Y., 2021b. Structural holes and R&D investment: evidence from top management teams of China's A-share listed firms. Appl. Econ. 53 (43), 4985–4999.
Wei, L., Yi, L., Xun, L., 2010. The evolution and influential factors of the innovation networks of local firms in a globalizing region-a comparative study between dolim group and elec-tech group in the pearl river delta, China. Econ. Geogr. 8 (30), 1316–1321.
Winter, A., Stäubert, S., Ammon, D., et al., 2018. Smart medical information technology for healthcare (SMITH). Methods Inf. Med. 57 (1), 92–105.
Wu, W., Li, N., Zhang, A., et al., 2016. Study on the impact of the innovation ability's Similarity,Coupling,and multidimensional proximity on the collaborative innovation in beijing-Tianjin-hebei between provinces and cities. Sci. Technol. Prog. Policy 9 (33), 24–29.
Xiao, J., Bao, Y., Wang, J., 2023. Which neighbor is more conducive to innovation? The moderating effect of partners' innovation. J. Technol. Tran. 48 (1), 33–67.
Xu, X., Huang, Y., Lai, Q., et al., 2023. Testing the stakeholders' partnership in a tourism waste management network: an ERGM approach. Environ. Sci. Pollut. Control Ser. 30 (6), 15335–15351.
Yan, L.L., Peng, J., Tan, Y., 2015. Network dynamics: how can we find patients like us? Inf. Syst. Res. 26 (3), 496–512.
Yaveroğlu Ö, N., Fitzhugh, S.M., Kurant, M., et al., 2015. ergm.graphlets: a package for ERG modeling based on graphlet statistics. J. Stat. Software 65 (12), 1–29.
Ye, G., Bi, C., 2020. An analysis of the development situation and trends of cross-regional scientific research collaboration under the perspective of knowledge exchange. J. Inf. Sci. 5 (39), 500–510.
Zeng, G., Liefner, I., 2019. Retrospect and Prospect of Research into China's Equipment Manufacturing-Innovation Network Introduction to the Theme Issue. Erdkunde, pp. 161–165.
Zeng, G., Liefner, I., Si, Y., 2011. The role of high-tech parks in China's regional economy: empirical evidence from the IC industry in the Zhangjiang High-tech Park, Shanghai. Erdkunde 65, 43–53.
Zhang, Z., Qian, D., 2022. Research on mobile health technological innovation situation in China based on patent datafrom 1985 to 2019. Med. Soc. 4 (35), 48–53.
Zhang, Z., Rao, W., 2021a. Key risks and development strategies for China's high-end medical equipment innovations. Risk Manag. Healthc. Pol. 19, 14–3037.
Zhang, Z., Rao, W., 2021b. Key risks and development strategies for China's high-end medical equipment innovations. Risk Manag. Healthc. Pol. 14, 3037–3056.
Zhang, L., Chen, W., et al., 2021. How do innovation network structures affect knowledge sharing? A simulation analysis of complex networks. Complexity 2021, 5107630.
Zhang, K., Qian, Q., Zhao, Y., 2020. Evolution of guangzhou biomedical industry innovation network structure and its proximity mechanism. Sustainability 12 (6), 2456.
Zhang, W., Mingyang, Z., Yuan, L., et al., 2021a. Social network analysis and public policy: what's new? Journal of Asian Public Policy 1–31.
Zhang, W., Zhang, X., Wu, G., 2021b. The network governance of urban renewal: a comparative analysis of two cities in China. Land Use Pol. 106, 105448.
Zhang, X., Yang, L., Zhang, X., et al., 2022a. Research on the development trend, evolution, and spatial local characteristics of the intelligent smart medical industry in the Yangtze River Economic Belt. Front. Public Health 10, 1022547.
Zhang, X., Dong, Y., Yi, T., 2022b. Digital economy,regional soft environment and formation of technology transfer network. Sci. Res. Manag. 43 (7), 124–134.
Zhao, Y., Wang, Q., Zheng, X., 2016. Impact of network vicinity and geographical proximity to knowledge transfer performance. Sci. Res. Manag. 1 (37), 128–136.
Zhao, K., Wu, Y., Liu, X., 2020. Research on the evolution characteristics and influencing factors of China's innovation cooperation network-A study by taking the cooperation of SCI papers as an example. Res. Manag. 7 (43), 96–105.
Zhou, Y., Li, Y., Liu, Y., et al., 2021. Network proximity and communities in innovation clusters across knowledge, business, and geography: evidence from China. IEEE Trans. Eng. Manag. 68 (5), 1388–1397.