Evolution of innovation networks in industrial clusters and multidimensional proximity: A case of Chinese cultural clusters

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ABSTRACT

The innovation and optimization of cultural industry clusters is important to the promotion of economic structural transformation and high-quality development. Taking 31 provinces (municipalities directly under the Central Government and autonomous regions in China) as the research object, the cross-sectional data included the number of joint patent applications for culture and related industries among provinces (regions) in 2014, 2016, 2018 and 2020. Then, the cluster innovation network was constructed using social network analysis (SNA) based on scientific identification of cultural industry clusters. This new cluster innovation network structure and its spatial evolution characteristics are accessible with the help of UCINet and ArcGIS tools. Finally, the multiple regression-quadratic assignment procedure (MR-QAP) method is used to determine the influence of geographical proximity, technological proximity, and social proximity on the evolution pattern of the cultural industry cluster innovation network. The results of the study are important for improving the efficiency of national cultural industry innovation and promoting regional synergistic development.

1. Introduction

Since the beginning of the 21st century, the cultural industry, with its powerful resource advantages and demand potential, has become an important starting point for the promotion of China's economic structural transformation and high-quality development. With the advent of a new era in global knowledge economy, resource elements with knowledge and technological innovation serve as the core and have become the new growth poles for promoting regional industrial development. Grasping the market rules and element conditions of cultural industry development and promoting the innovative development of regional cultural industry clusters are necessary to further the prosperity of China's cultural market and enhance international competitiveness. In recent years, China's cultural industry has rapidly developed in scale, intensification and digitization. In 2019, the national added value of cultural and related industries, such as tourism, as well as digital, mobile and social media, also accounted for 4.5% of GDP, up 0.53 percentage points from 3.97% in 2015 (United Nations Conf. on Trade and Development 2018). In 2020, the national operating revenue of cultural and related industry enterprises was RMB 985.14 billion, up 2.2% from 2019, based on rapid recovery to positive growth under the heavy impact of the global epidemic. In May 2021, the National People's Congress (NPC) "Fourteenth Five-Year Plan" for the development of cultural industries pointed out that: "A number of cultural industry parks and bases with distinctive features, prominent main industries, high concentration and strong drive will be reasonably laid out in the country to promote the transformation of the park from a space for the gathering of elements to a platform for innovation and development." With the support of major national development strategies, "innovation" is becoming a driving force to highlight the characteristics of the Chinese cultural industry clusters, and the innovation activities of the cultural industry are gradually moving towards more diversified and deeper development. The innovation network of cultural industry clusters has transformed the industry from a single linear network to a network wherein multiple subjects interact synergistically.

With the frequent exchange of knowledge and industrial innovation resources between organizations and regions, the innovation networks are gaining strength through unity of purpose (Cammarano et al., 2016). The spatial agglomeration of cultural industries not only encourages the geographic gathering of related industries and institutions, but also promotes both social and knowledge connections among participants. These interactions will increase the relevant proximity effects based on geographic, social, technical, and knowledge connections (Aldieri, 2011). Although the development of China's cultural industry has been
increasing in recent years as a percentage of the total national economy, when compared with other countries with higher levels of cultural industry development, China’s cultural industry is at a lower level in terms of total volume and scale. This results in an insufficient capacity for independent innovation in the cultural industry and obvious disparities between regions. Data from the World Intellectual Property Organization show that, cultural industries in the United States account for about 15–30% of GDP. In Europe, it averages between 10 and 15 percent, and in Japan, it is about 20 percent (Ji, 2016). The major developed countries (regions) in the world have elevated the development of cultural industries to the strategic level of national (regional) competitiveness and concentrated their efforts on developing advantageous cultural industries. In the evolutionary process of China’s cultural industry cluster development, the local embedded characteristics of industry clusters can weaken the linkage between the power elements of the cultural industry and the competitive drive of urban agglomeration (Song et al., 2021).

Regional disparities in the network are specifically characterized by the heterogeneity (or diversities) within the network structure formed by each node. The geographical, social, cognitive or technological proximities are the basis of the innovation network structure’s heterogeneity. These proximity factors are the key to the evolution of the innovation network’s connectivity and spatial patterns. The questions that need to be answered concerning how to connect and strengthen this diverse innovation network are: What is the shape of the innovation network of Chinese cultural industry clusters at this stage? How can we make use of the multi-dimensional proximity factor to bring into play the comparative advantages of each node in the innovation network? Finally: How can we use these advantages to promote the reasonable flow and efficient concentration of the innovation resources and factors in the cultural industry? There is an urgent need to answer these questions in order to explore the proximity factors conducive to the structural optimization of the cultural industry innovation networks. The answers will help to effectively promote the transformation and upgrading of cultural industry clusters, and they can provide meaningful lessons for the development of the cultural industry’s innovation clusters in other developing countries.

The following Section 2 provides a brief literature review followed by an explanation of how this paper is organized. Section 3 shows how data are used to answer the questions that define the objectives of this paper. Section 4 defines the evolutionary features of the innovation components that make up the structure of Chinese cultural industry clusters, Section 5 analyzes the multidimensional proximity factors of innovation networks followed by the paper’s conclusion, which provides a summation of this paper’s important contributions and insights.

2. Literature review

The innovative development of cultural industries is highly dependent on market activities, and they are also characterized by significant agglomeration and networks compared to traditional industries (Gibson and Kong, 2005). Initially, scholars believed that the “flexible specialization” of the cultural industry was the key factor that gave it a network character. The cultural industry as a whole should be considered on a global level since the industry is becoming more multicultural and producers in different countries are often anxious to reach to a more global audience (Marvasty and Canterbery, 2005). The vertical separation of the Hollywood film industry has brought attention to the “elastic specialization” of the industry’s production method, which has promoted the agglomeration of enterprises, and in turn has facilitated the spread of film development to increased regions (Storper, 2004). As the characteristics of cultural industry clusters become increasingly prominent, the production and innovation of clusters are more dependent on the communication and interaction between subjects within the clusters. This interaction occurs according to the linkages within the cluster and its organizational network structure (Macgregor and Madsen, 2018). The Hollywood animation industry is a network of a few large companies and a large number of small companies working together with the movie giants. They also have close ties to the independent production companies and small companies working with a number of film conglomerates (Scott, 2002). It is also important to study the participants in the innovation network. Yusuf and Nabeshima (2005) considers the auxiliary sector as an essential part of the production network, such as education and training institutions, consulting services, visitors, research units, etc., which provide support and complementary services to the cultural industry. For multi-subject clusters, the innovation network among clusters is not a single-level linkage, but a complex system of multi-level network interactions.

Based on the study of network connections and subject participation in cultural industries, scholars have gradually regrouped the importance of the significance brought by the network of vision. Scott(2011) argues that clustered firms form multiple interactions in collaboration, and that such interactions can inspire innovation and promote new ideas. Lee (2011), in a study of the UK television production industry, points out that the network structure facilitates communication and innovative practices between companies, and enhances their core competencies. The sharing, integration, and application of technological knowledge among cultural cluster companies greatly enhances the overall knowledge and innovation capacity of the cluster (Yu and Tang, 2020).

Along with the in-depth research on innovation networks of cultural industry clusters, the causes of interactive behavior among network subjects have also received attention from many scholars who have explored how to build cooperative relationships to improve innovation through empirical research (Kumar and Zabreer, 2019; Cabral and Pacheco-de-Almeida, 2019). Network proximity refers to similar characteristics of actors in different aspects; moreover, the utilization of multidimensional proximity factors can improve cooperation efficiency and the competitive advantage (Broekel, 2015; Geldes et al., 2015). Evolutionary economic geographer Boschma (2005) proposed a multidimensional proximity research framework from a relational perspective that includes five dimensions: cognitive proximity, organizational proximity, social proximity, institutional proximity, and geographic proximity. Based on an empirical study of London and Berlin, Heur (2009) describes how the production networks of cultural and creative industries are influenced by local networks of relationships. Wu et al. (2021) also proposed that the cluster network space is not only a geographical space for industrial agglomeration, but also a space where economic, social and institutional factors are intricately linked, showing the interaction and coupling of economic, social, cultural and institutional multidimensional spaces. Typical examples include the film industry in Los Angeles, the publishing and advertising industries in London, and the audio-visual and animation industries in Tokyo. This spatial agglomeration of multidimensional factors is extremely important for the development of innovation capabilities.

In summary, existing studies on innovation networks in cultural industry clusters offer more multi-dimensional ideas and references for this study. First, the unique and flexible production mode of cultural industry can promote a close connection among industries, thereby presenting a complex and multi-level network structure in the cluster process. Second, studying the development of innovation network clusters in cultural industries is the key to successful promotion of an optimized cultural/industrial structure, improving resource integration efficiency and narrowing regional disparities. Third, economic, social and geographical factors are important factors affecting the development of innovation networks in cultural industry clusters. However, there are still shortcomings in existing studies.

This study introduces the following approach to a more innovative industrial/cultural clustering based on previous studies. First, the definition and identification of the degree of industrial/cluster development needed in the study area is added before the social network is analyzed, which makes up for the neglect of the influential relationship between industrial clusters and innovation networks in traditional studies. This approach allows a clearer and more comprehensive presentation of the
complex, multi-level network structure generated in the cluster process. Secondly, scholars have mostly applied the analysis of multidimensional proximity to mature industries such as manufacturing and service industries, but the analysis of these mature industries and their proximity to the innovation networks of cultural industry clusters bridges a knowledge gap. Based on the characteristics of agglomeration, innovation and local embeddedness of cultural industries, this study systematically considers the influence of geographical proximity, technological proximity, and social proximity on the innovation networks of cultural industry clusters. To discover the break-through point of the cultural industry cluster innovation network development in a targeted manner is a goal worth achieving, but to determine more applicable and operable solutions for the development of cultural industries in other developing countries is essential to the dissemination of a global cultural movement that can benefit society as a whole.

3. Data sources and research methods

3.1. Data sources

As the main form of R&D output, a patent is the core index to measure industrial development and innovation ability. A joint patent application is the result of cooperation in information sharing as well as knowledge exchange among innovation project participants, which can fully reflect the innovation development relationship between cooperative applicants and is widely used in the study of innovation networks (Zhou et al., 2021). To ensure the availability and completeness of the patent data and its effectiveness, the data from 2014 was included in China’s first cultural industry statistical yearbook as the historical starting point. The yearbook more clearly reflects the structural evolution characteristics through patenting of the cultural industry among regions. The patent-inclusive yearbook became a biannual source of data designed to serve as a cycle analysis node. That is, this paper uses the number of patents for cultural industry cooperation in 31 provinces, autonomous regions and municipalities directly under the Central Government of China (excluding Hong Kong, Macao and Taiwan) in the 2014, 2016, 2018 and 2020 years as panel data. Patent data are obtained from the industrial patent information service search platform of the China National Intellectual Property Office (CNIPA), and data are collected based on setting keyword information such as filing date, applicant (patentee) and IPC classification number to form a search formula. The main steps are as follows: (1) Enter the search formula (filing date = xxxx AND applicant (patentee) = (xx AND xx) AND IPC classification number = (xxx)). (2) Eliminate the cooperation patents whose applicants are duplicates of two regions, the number of cooperation patents among the 31 provinces (municipalities directly under the Central Government and autonomous regions) was finally screened out to be 2,871 in the four sub-years studied. Data related to the cultural industry is in the cluster development section obtained from the China Culture and Related Industries Statistical Yearbook.

3.2. Industrial cluster location entropy

Reflecting the scale and agglomeration of industrial development by measuring the degree of industry specialization is the usual means of identifying industrial clusters. Given the availability of data on China’s cultural industry, we chose to construct the locational entropy coefficient (LQij) of the cultural industry practitioners to examine the scale of development and innovation agglomeration of China’s regional cultural industry. According to Song et al. (2021) and Scott (2006), the equation of the article on industrial agglomeration is as follows:

\[ \text{LQ}_{ij} = \left( \frac{p_j}{p} \right) / \left( \frac{P_j}{P} \right) \]  

(1)

where \( p_j \) denotes the employees of industry \( j \) in region \( i \); \( p_i \) denotes the employees of all industries in region \( i \); \( P_j \) denotes the employees of industry \( j \) nationwide; and \( P \) denotes the employees of industries nationwide.

3.3. Social network analysis (SNA)

Social network analysis (SNA) is mainly used to analyze the structure of the network relationship between different social agents and the network’s attributes. SNA can scientifically quantify the interaction between innovation agents and scholars in the field of regional economy; thus, its predominant function is to introduce the value of SNA into the innovation network research (Ter Wal and Boschma, 2009). To more objectively reflect the overall structural characteristics of the innovation network of cultural industry clusters, network density, average path length and a clustering coefficient were selected as the measures of the overall network characteristics (Liu, 2004; Mitze and Strotebeck, 2018; Wang et al., 2019). The measurement of centrality is the key to SNA analysis, and the measurement of centrality can reflect the most influential and important nodes in the innovation network linkages (Freeman, 1979; Wasserman, 1994; Nepelski and De Prato, 2018). The specific calculations are in the next section.

3.3.1. Overall network characteristics

(1) Network density: This type of density is used to reflect the tightness and cohesiveness of the innovation network. The higher the density value, the stronger the cohesiveness of the network nodes and vice versa. According to Freeman (1991), Nepelski and De Prato (2018), the equation for the density value (D) is as follows:

\[ D = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=i}^{n} x_{ij} \]  

(2)

where \( x_{ij} \) represents the network relationship that exists between city \( i \) and city \( j \). If it exists, it is 1; if it does not exist, it is 0. \( n \) represents the number of cities in the innovation network.

(2) Average path length: This length represents the mean of distance (the shortest distance) of all nodes in the network, which can reflect the separation and accessibility degree of all nodes in the network. Based on the studies of Li et al. (2014), the specific formula is as follows:

\[ L = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=i}^{n} d_{ij} \]  

(3)

where \( d_{ij} \) represents the path distance between city node \( i \) and city node \( j \), and \( n \) represents the number of city nodes in the network.

(3) Clustering coefficient: This coefficient is used to characterize the local aggregation among the nodes in the network, the equation is expressed as follows (Yustiawan et al., 2015):

\[ C_i = \frac{2E_i}{k_i(k_i-1)} \]  

(4)

where \( k_i \) represents the number of nodes adjacent to a city node \( i \); \( E_i \) represents the actual number of connected edges of the subnetwork composed of nodes adjacent to city node \( i \).

3.3.2. Individual network characteristics

(1) Degree centrality: This represents the number of nodes directly connected to a city node, divided into absolute degree centrality
and relative degree centrality. According to Freeman (1979), the specific formula is as follows:

\[ d_i = \sum_{j \neq k} d_{ij} \quad d_i = \frac{d_i}{n-1} \]  

(5)

where \( d_{ij} \) denotes whether node \( i \) is directly connected to \( j \). If there is a direct connection, it is 1; if there is no direct connection, it is 0. \( n-1 \) represents the maximum possible degree of any one node.

(2) Intermediate centrality: This indicates the strength of a node’s ability to control the relationships of other nodes. The greater the centrality is, the more central the position of the node in the network. Based on the studies of Xie and Song (2020), the formula is as follows:

\[ CD_i = \sum_{m} \sum_{n} P_{mn}(i) / P_{mn} , \quad m \neq n \neq i , \quad m < n \]  

(6)

where \( P_{mn} \) represents the number of shortest paths between node \( m \) and node \( n \), and \( P_{mn}(i) \) is the number of shortest paths between node \( m \) and node \( n \) that pass through node \( i \).

(3) Closeness Centrality: Also known as overall centrality, it characterizes the sum of the shortest paths between nodes. The larger the closeness centrality is, the farther away the node is from the core node of the network, and vice versa. The formula is as follows (Xie and Song, 2020):

\[ FD_i = \sum_{j=1}^{n} d_{ij} \]  

(7)

where \( d_{ij} \) denotes the length of the shortest path between node \( i \) and node \( j \).

3.4 Multidimensional proximity variable selection

(1) Geographic proximity: Studies measure geographic proximity by weighting patent output in other regions. According to Funk (2014), the specific formula is as follows:

\[ Geo_i = \sum_{j \neq i} \frac{NP_i}{1 + GD_i} \]  

(8)

and

\[ GD_i = R \{ \arccos \left[ \sin \beta_i \sin \beta_j + \cos \beta_i \cos \beta_j \cos (\alpha_i - \alpha_j) \right] \} \]  

(9)

where \( NP_i \) denotes the number of patent applications for cultural industry in region \( j \) in year \( t \); \( GD_i \) denotes the geographical distance between region \( i \) and region \( j \). \( R \) is the radius of the earth with 6371 km as the base; \( \beta_i \) and \( \beta_j \) represent the latitude of region \( i \) and region \( j \), while \( \alpha_i \) and \( \alpha_j \) represent the longitude of region \( i \) and region \( j \).

(2) Technological proximity: This type of proximity refers to the similarity or relatedness of the knowledge base or technological structure among cities. Based on the studies of Zhang and Qian (2021), the equation is expressed as follows:

\[ Tec_i = \frac{\sum(X_{in}X_{jn})}{\sqrt{(\sum X_{in}^2)(\sum X_{jn}^2)}} \]  

(10)

where \( X_{in} \) and \( X_{jn} \) denote the number of applications between region \( i \) and region \( j \), regarding \( n \) types of patents. The technical proximity \( Tec_i \) takes the value between 0 and 1. The closer the value is to 1, the higher the technical association of the network subjects is, and vice versa.

(3) Social proximity: This type of proximity refers to the social embeddedness between network subjects, usually measured by the number of collaborations or the inverse of the shortest distance between two nodes. According to Ahuja (2009), the equation for social proximity is expressed as:

\[ Soc_i = \frac{K_i}{\sum K_i} \]  

(11)

where \( K_i \) represents the number of joint patent applications between the innovation subject \( i \) and innovation subject \( j \). The social proximity \( Soc_i \) takes a value between 0 and 1. If the value tends to be closer to 1, it indicates that the social relationship of the network subjects is tighter and vice versa.

4. Evolutionary features of the innovation network structure of Chinese cultural industry clusters

4.1. Cultural industry cluster identification

Industrial clusters represent the localized networking process of industries based on specialized agglomeration; thus, identifying industrial clusters is an important prerequisite for analyzing the structure of industrial innovation networks. This paper presents the spatial distribution of locational entropy of Chinese cultural industry in node years based on locational entropy measurements of cultural industry practitioners in China from 2013 to 2018. The presentation is enhanced visually with the help of ArcGIS software, which clarifies the development course and evolutionary characteristics of Chinese cultural industry clusters. This node-year based approach lays the foundation for the scientific analysis of the Chinese cultural industry clusters innovation network, as shown in Figure 1. According to the figure, the provinces with a high level of cultural industry agglomeration in China are mainly located in the eastern and central regions. In 2013, the regions with the locational entropy of China’s cultural industry above 1 were Beijing, Shanghai, Guangdong, Tianjin, Jiangsu, Fujian, Zhejiang, and Hunan. In 2018, the regions with a locational entropy above 1 were Beijing, Guangdong, Shanghai, Jiangsu, Fujian, Zhejiang, Chongqing, and Hunan. Finally, 25 provinces municipalities and autonomous regions (in Beijing, Shanghai, Guangdong, Jiangsu, Fujian, Zhejiang, Shandong, Jiangxi, Hebei, Shannxi, Henan, Liaoning, Anhui, Hebei, Qinghai, Hainan, Tibet, Sichuan, Shanxi, Ningxia, Guangxi, and Inner Mongolia) were selected based on their ranking as key reference objects by analyzing China’s innovation network of evolutionary cultural industry cluster characteristics.

4.2. Innovation network structure characteristics

Optimizing China’s innovation development of cultural industry clusters requires a basic understanding of the formation and evolution of the regional network structure. Thus, we must stay within the context of the cultural industrial innovation network’s research paradigm, which follows: Using UCIINet software, the number of joint patent applications of cultural and related industries in 31 provinces (municipalities and autonomous regions) of China in four cross-sections from 2014, 2016, 2018 and 2020 were selected for our social network analysis (SNA), and a 31 × 31 matrix of the inter-regional cooperation network was constructed to obtain the overall structural indicators and individual structural indicators of innovation networks.

Calculation results in Table 1 show an increase in the number of innovative subjects in China’s cultural industry innovation network from 24 to 31. Furthermore, the number of relationships increased from 84 to 196 from 2014 to 2020. Notably, 31 innovative subjects in 2020 indicate that all provinces (regions) can produce different cultural industry innovation network behaviors, and the cooperative behaviors among subjects are multiplying. Network density grew from 0.09 to 0.211, with
an overall growth trend, but the innovation network density is still low, and the interaction between nodes is not close enough. The average degree of innovation network changed from 2.71 in 2014 to 6.323 in 2020, with the larger growth, indicating that the innovation connection between the nodes of the Chinese cultural industry innovation network is getting closer, and the degree of connection is growing from an average of 2 to an average of 6 nodes. The sparse innovation network of cultural industry is gradually changing to a denser and more complex network structure.

In terms of clustering coefficient and average path length, the clustering coefficient fluctuates around 0.5, and the average path length decreases year by year, but both values tend toward 1. The innovation network structure of China's cultural industry clusters shows the characteristics of "aggregation" and "small world" development, representing a more open communication and cooperation channel between the network nodes.

According to the structural level and the degree of subject connection to the innovation network system, the innovation system can be divided into core layer, auxiliary layer and edge layer (Jiang and Xu, 2014). We obtained results of individual characteristic indexes from China's cultural industry innovation network by calculating the centrality degree of network nodes. As shown in Table 2, the top five provinces (regions) in centrality ranking from 2014 to 2016 include Beijing, Shanghai, Tianjin, Jiangsu, and Zhejiang. The top five provinces (regions) in centrality ranking in 2018 are Beijing, Shanghai, Jiangsu, Zhejiang, and Guangdong; the top five provinces (regions) in centrality ranking in 2020 are Beijing, Shanghai, Zhejiang, Jiangsu, and Shandong. Based on the overall ranking situation, combined with the results of the Chinese cultural industry cluster identification, a schematic diagram of the innovation network structure levels of the Chinese cultural industry clusters is drawn. Figure 2 shows Beijing to be the core layer of China's cultural industry innovation network. The auxiliary layers are Shanghai, Jiangsu, Zhejiang, Guangdong and Shandong, and the edge layers are the remaining provinces (autonomous regions and municipalities directly under the central government). Therefore, the innovation network level of 25 cultural industry clusters is consistent with the overall structural characteristics and individual characteristics of the network. Moreover, the innovation network density is relatively high among regions with higher agglomeration levels, and provinces with top individual centrality rankings are included in the target clusters. Specifically, the innovation network of China's cultural industry clusters shows a development trend of a gradually expanding network scale; however, the overall network density is still low. With the increasing innovation connection among network subjects, the cluster innovation network shows the development
characteristics of agglomeration and small-worldness. Regions with a high level of cultural industry agglomeration are located at the core or auxiliary level in the innovation network, which are the key nodes and important supports constituting the innovation network of China's cultural industry clusters.

4.3. Innovation network evolutionary characteristics

Based on the structural characteristics of the innovation network of Chinese cultural industry clusters, ArcGIS software tools were used to visualize the innovation level of the Chinese cultural industry clusters and the spatial evolution pattern of the innovation network in 2014, 2016, 2018 and 2020. The results are shown in Figure 3. The results of the study found that:

(1) **The overall scale** of China's cultural industry cluster innovation network is expanding, forming a “radial” spatial structure with Beijing as the core and Shanghai as the center of gravity. With the evolution and development of China’s cultural industry clusters, the number of innovation subjects in China’s cultural industry clusters is increasing; the innovation cooperation among subjects is becoming increasingly frequent, and the scale of innovation network is gradually expanding. Beijing and Shanghai have developed into network hubs, and through cooperation with other key nodes, they form the backbone of the innovation network connecting China's cultural industry clusters. This network gives full play to the leading role and connectivity function of the network's core innovation, which provides the leadership and collaboration needed to strengthen the innovation development of China's cultural industry clusters. In 2020, the number of joint patent applications in the cultural industries of Beijing and Shanghai have accounted for 45.9% of the national ratio. In 2020, the number of joint patent applications in the cultural industries of Beijing in 2020 was five times higher than in 2014. Notably, the number of joint patent applications in the cultural industries of Shanghai has always exceeded that of the other cities. As a national cultural center, Beijing has always focused on the high-quality development of its own cultural industry and strengthened innovation cooperation with other provinces and regions. Beijing's prominent position in strengthening the connection of the national innovation network is an leader in creating capital. Beijing has a wide range of innovation cooperation in the cultural industry and the spatial layout of its innovation network covers almost all parts of the country, maintaining close contact with the east and central regions and a high level of innovation. Meanwhile, the level of innovation cooperation with cultural industry in western regions is low, but the density of innovation cooperation is in a stable state. In terms of innovation intensity, Shanghai, as a national financial center, has the strongest connection with other regions in the cultural industry innovation network. In addition to Beijing, Shanghai maintains a very stable and high level of cultural industry innovation through cooperation with Zhejiang, Jiangsu and Guangdong in that order. Notably, Zhejiang, Jiangsu and Guangdong are the top three recipients of new patents in the country.

(2) **China’s cultural industry clusters** are becoming increasingly connected and complex, and the development trend of “preferential connection” of cluster networks is becoming increasingly obvious.

From the spatial evolution characteristics of the innovation network of Chinese cultural industry clusters, the network structure gradually develops from a monocentric to a complex mode. The connection between the cluster innovation network subjects becomes increasingly frequent, and the level of joint innovation among the clusters also increases. At the same time, the innovation cooperation among the network subjects of the Chinese cultural industry clusters has a more obvious structural growth trend. This new growth is evidence of "connecting on the basis of merit, strong cooperation, and the strongest getting stronger." The subjects with higher cooperation intensity are mainly concentrated among Beijing, Shanghai, Jiangsu, Zhejiang and Guangdong. For
example, Shanghai, as the center of gravity for the innovation network of cultural industry clusters in China, has the highest level of joint innovation cooperation with Jiangsu, Zhejiang and Guangdong, with their share of joint patent application in Shanghai’s cultural industry accounting for 68.62% of the total patents. Meanwhile, Jiangsu, Zhejiang and Guangdong continue to rank among the top three in the country in terms of the number of patents granted to cultural and related industries. Among the innovation ties between Beijing and other nodes, the innovation cooperation with Shanghai accounts for 20%, and the cooperation between network core and the network center of gravity can enhance the scale of the overall cultural innovation network ties. Clearly, the innovation cooperation between the innovation networks of cultural industry clusters is predominantly based on the innovation ability or resource conditions of subjects; hence, the more superior the innovation resource conditions are and the stronger the innovation ability of the cluster nodes, the more attractive they are to other innovation subjects. By strengthening the spatial flow of cultural innovation information elements among subjects, such network linkage groups continuously form a virtuous cycle of cumulative effect. This cycle enables self-reinforcement, as the participants accumulate innovation network resources and capital. However, the overriding goal is to always work to establish innovation network linkages with other regions. Once they fully consolidate, they can help regulate growth and assume a leadership role in the network, thereby improving the cooperation and development of the overall cultural industry cluster innovation network.

(3) The inter-regional gap in the level of innovation network of Chinese cultural industry clusters is obvious, and a heterogeneous space of “core-edge” is formed in the East and West regions. From the spatial structure of the innovation network evolution characteristics, the eastern cluster innovation network density is heavier and the cooperation level is higher; while the central and western regions innovation network density is lighter and the overall cooperation level is lower. The overall network development trend from east to west is gradually decreasing. Specifically, the eastern region shows an innovation network with Beijing as the spatial core, and Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong and Shandong as the main spatial nodes. In the central region, except for Anhui and Hunan, and in the western region, except for Shaanxi, all other spatial nodes are at a low level of innovation network intensity and innovation achievements. The low-level node cities include Gansu, Yunnan, Qinghai, Tibet, Ningxia, Heilongjiang and Hainan. The low level ratings are at the periphery of the innovation network. In terms of cross-regional networks, the east-central cluster’s cultural industry innovation network has higher intensity, medium density, and a smaller spatial span, forming three axes located in the Beijing-Anhui, Shanghai-Hubei, and Shanghai-Chongqing regions. The linked subjects within the innovation network are concentrated between the core regions, and the distribution of network nodes is stable but uneven. The innovation network between east and west has medium strength, high density and large spatial span, forming two axes—in the Guangdong-Xinjiang and Beijing-Xinjiang areas. Figure 3 shows that the innovation linkage and cooperation level between the eastern clusters and western regions have increased significantly. The innovation network between the central-west, central-medium, and west-west sections have extremely low strength and a small spatial span. Except for generating low-density network linkages, the innovation cooperation between the west and other regions and between each other is almost zero. In general, the spatial evolution of the innovation network among
the Chinese cultural industry clusters follows the law of regional hierarchy development and shows the overall spatial layout and evolution characteristics of strength in the eastern regions and weaknesses in the western regions, as well as strength inside the hierarchy and weakness outside the hierarchy.

5. Analysis of multidimensional proximity factors of innovation networks

To verify the degree of influence of multidimensional proximity factors on the cooperation of innovation networks in Chinese cultural industry clusters at different cycle stages, QAP multiple regression analysis was applied to incorporate geographic proximity, technological proximity, and social proximity factors into the analysis model and thereby explore their relationships with cluster innovation networks. To ensure the accuracy of the model calculation, the analysis was set up with 5000 random permutations as well as a correlation analysis and inclusion of robust standard errors. The regression results are shown in Table 3.

According to the calculation results, Table 3 shows that in 2014, both social proximity and geographical proximity passed the 1% significance level test with unstandardized coefficients of 8.356 and 0.719, respectively. Notably, technological proximity had not yet passed the significance level test, indicating that the innovation interactions between Chinese cultural industry clusters at this stage are more inclined to knowledge cooperation based on social ties. Thus, the cultural industry clusters have tended to facilitate the transfer and exchange of innovation resources in the clusters’ cultural industries by establishing trusting relationships with each other. An example is two technological participants in the same or neighboring area choose to jointly innovate due to having similar customs, social systems or stable cooperative relationships. Secondly, geographical proximity is used to strengthen the connection between the innovation subjects. The closer the geographical distance is, the closer the innovation cooperation relationship is (Schilling and Phelps, 2007). Cultural innovation network subjects choose other subjects with suitable spatial distance and transportation time to promote the development of innovation in cultural industry clusters by shortening the distance of knowledge transfer and reducing the cost of knowledge exchange and diffusion. This type of activity is similar to the establishment of industrial parks formed by each related enterprise due to geographical clustering. The role relationship between the cluster innovation network and technological proximity is not significant, indicating that the innovation cooperation of the Chinese cultural industry clusters at this time but does not focus on knowledge understanding and absorption among subjects, paying less attention to the similarity in professional knowledge and experience. Instead, they focus on methodological and technological dimensions when selecting subjects for cooperation.

The 2016 results show that social proximity has the highest level of significance, with the unstandardized coefficient growing to 14.851 and passing the 1% significance level test. Next in order of significance is the geographical proximity, which passes the 10% significance level test and is significantly lower compared to 2014. Finally, technological proximity has no significant effect but has improved compared to 2014. During this period, the development of innovation networks in the Chinese cultural industry clusters is most closely related to social proximity, indicating that the social trust relationship of cluster subjects remains the most critical influencing factor, and innovation subjects will choose partners with established cooperative relationships for innovation linkages. Meanwhile, geographical proximity also affects the development of innovation networks in the Chinese cultural industry clusters to some extent. This is possible because spatial distance and transportation distance are still considerations for cultural innovation subjects when choosing cooperation and exchange options. However, their moderating effect decreased significantly compared with 2014. In this stage, the effect of technological proximity factors on the cooperation of cluster innovation subjects remains insignificant, probably due to the large gap in innovation technology levels between subjects and the low overlap of technological bases, which affects the knowledge resource sharing and technology exchange as well as the cooperation among innovation network subjects.

The results in 2018 show that social proximity, geographical proximity and technological proximity all had significant effects on the innovation network of the Chinese cultural industry clusters, and social proximity had the highest significance level, passing the 1% significance test, followed by technological proximity and technological proximity, passing the 5% significance test. In this period, social proximity had the same results as noted in the first two periods. Stable cooperative relationships can strengthen the trust between cultural innovation subjects, thereby improving the possibility of cultural innovation subjects choosing to exchange and cooperate. At this time, technological proximity changes are the most obvious, and the non-standardized coefficient can substantially increase, which can affect both cooperation and exchange among cultural innovation subjects. The increases in cooperation and exchange shows a trend toward improvement of the industrial innovation technology level of the Chinese cultural industry’s cluster subjects. As the methodological technologies gradually converge with each other, the understanding and absorption of knowledge exchange increasingly enhances mutual interests in technical level factors, R&D potential and similarities in methodologies when cooperating. As for the geographical proximity in this period, the degree of its influence on the development of innovation networks gradually decreased, indicating that transportation and the speed of knowledge dissemination are no longer key factors affecting interactions that can benefit innovation cooperation. The factors affecting this cooperation are most likely due to a reduction in the various cost issues arising from geographical distance with the development of modern communication technologies and a greater variety of transportation modes.

The results in 2020 show that social proximity and technological proximity have significant effects on the development of innovation networks in cultural industry clusters, where social proximity still passes the 1% significance test, and technological proximity passes the 5% significance test. Moreover, no significant effect was recorded based on geographical proximity. During this period, mature and stable trust in established social relationships are always the most critical factor for the
Chinese cultural industry's cluster subjects when choosing innovation cooperation. The importance of technological proximity increased significantly during this period, indicating that similar technological innovation levels and knowledge communication skills could be shared among network subjects thereby advancing the development of the cluster innovation network. Together, they could overcome technological challenges while maintaining competitive advantages by promoting knowledge exchange and sharing. In 2020, geographical proximity did not play a moderating role in the development of the Chinese cultural industry clusters. This indicated that the security, convenience, and low cost of modern communication and transportation technologies was more obvious than before, and the establishment of various types of fully functional network technology, such as videoconferencing, with their cooperation platforms made the networks linked by geographical proximity weaker and weaker, and their advantageous roles were gradually replaced.

Overall, from 2014-2020, the development of innovation networks in the Chinese cultural industry clusters was always significantly influenced by social proximity factors, with the influence of technological proximity playing an increasingly prominent role, and the effects of geographical proximity gradually weakening. This shows that solid social cooperation relationships can effectively promote Chinese cultural industry cluster innovation subjects to communicate and cooperate using patented technologies. This phenomenon corresponds to the evolutionary feature of obvious interregional disparity on the level of Chinese cultural industry cluster innovation networks, where the relationship bases such as similar corporate cultures, common strategic visions, and reliable trust networks motivate subjects to choose cooperation partners with comparable development levels to reduce communication risks and strengthen innovation ties. The increasing role of technological proximity is closely related to the development trend of merit-based connection in cluster networks. The key to technological proximity lies in the ability of innovation subjects to disseminate and absorb knowledge, and the high degree of technological similarity and matching makes knowledge exchange more efficient and convenient, thereby enhancing the innovation connection of network subjects; The large spatial span presented by the innovation network of the Chinese cultural industry clusters confirms the gradual weakening of the geographical proximity advantage due to the emergence of modern network cooperation platforms that break the spatial barriers among innovation subjects, so that the cost of cooperation over long distances no longer limits and affects the expansion and close development of the innovation network of Chinese cultural industry clusters.

6. Conclusion and outlook

This paper systematically analyzes and visualizes the structural characteristics and spatio-temporal evolution process of the innovation network of Chinese cultural industry clusters based on the scientific identification of Chinese cultural industry clusters. This process relies on the number of patents granted for cultural industry cooperation. The QAP multiple regression analysis is also used to introduce multidimensional proximity factors to explain the evolutionary motives of the innovation network pattern of cultural industry clusters. Specifically, the following conclusions were obtained:

Structurally, the cluster innovation network shows a network structure with Beijing as the core layer, Shanghai, Jiangsu, Zhejiang, Guangdong and Shandong as the auxiliary layer, and the rest of the provinces and regions as the peripheral layer. The cluster innovation network structure presents the characteristics of aggregation and small world development, as well as the more unobstructed communication and cooperation channels between network nodes. The connection between nodes of the innovation network is getting closer, and the centrality of each regional innovation network is constantly improving. Therefore, the cluster innovation network should be strictly based on the law of cluster innovation development, which is based on the resources and comparative advantages of the cultural industries in each region. The process gives full play to the leading and radial-driven role of the core nodes and promotes the reasonable flow and efficient gathering of cultural innovation resource elements between regions (Wu et al., 2015). The goal is to build a cluster innovation network with complementary advantages for high-efficiency and high-quality development.

In terms of the evolutionary characteristics of the innovation network, the innovation network of China's cultural industry clusters shows a radial spatial development structure. Moreover, the development trend of preferential connections within the cluster innovation network is becoming increasingly obvious, as the heterogeneous spatial pattern of the core-edge is gradually formed in the eastern, central and western regions. With the gradual expansion designed to exceed the scale of China's innovation network. Currently, the spatial evolution of the innovation network of China's cultural industry clusters follows the development law of regional hierarchy, showing the overall spatial layout and evolutionary characteristics of strong in the east and weak in the west, strong inside and weak outside, as well as the "core-edge" phenomenon, which is gradually weakening, but the regional gap is still obvious. Therefore, the governments of provinces and regions should also formulate various incentive policies to encourage R&D subjects to actively participate in cultural industry. Technical and financial support should be given to regions with cultural resource advantages but poor foundation. The goal of effectively narrowing the gap in cluster innovation development is achieved, thus providing balanced support for both strong and weak participants.

From the perspective of multi-dimensional proximity factors, social proximity has always been a key factor influencing the development of innovation networks in Chinese cultural industry clusters. With the emergence of modern network cooperation platforms, the influence of geographical proximity on the innovation networks of clusters is no longer important, and the cost of cooperation over long distances is no longer a factor that constrains the expansion as it closes the development of China's innovation network cultural industry clusters. Therefore, social proximity and technological proximity are particularly important to promote the development of cluster innovation networks. To maintain stable, social cooperation, cluster innovation subjects should pay attention to enhancing the cultivation of innovation consciousness within the network and continuously strengthen the understanding and absorption ability of innovation knowledge.

Finally, the research on the generation and evolution of the cultural industry innovation network from the perspective of multidimensional proximity is a complex and systematic work involving the development of each innovation subject itself. The network encourages collaboration among subjects and supports the internal and external environment of the network. However, this article is limited by the level of research and the availability of data for a single research sample. The problem is exacerbated by insufficient criteria and measurement methods for defining multidimensional proximity dimensions. The patent data selected in this study only show the phenomenon of cooperation between regions. In order to consider the existence of multiple subjects in innovation networks, more comprehensive and time-sensitive data must be selected for empirical verification by adding cooperation data, such as papers and research projects, in the subsequent study. In addition, this study confirms the previous research by scholars when exploring the evolution of innovation networks on a national scale (Zhang et al., 2020). However, in terms of geographical spatial scale, the industrial structures and development contexts of different countries should be considered (Proost, 2019), and the multidimensional proximity interactions should be discussed to condense a richer conclusion on the evolution of innovation networks. In this way, it comprehensively reflects the current situation and trends of innovation network proximity in cultural industries, thereby revealing suggestions for industrial structure optimization that are more useful as exemplary references for other countries.
Declarations

Author contribution statement

Jiamin Liu: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Yongheng Fang: Conceived and designed the experiments; Wrote the paper.

Yihan Chi: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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Data availability statement

Data associated with this study has been deposited at https://www.cnipa.gov.cn/coll/col61/index.html
http://www.stats.gov.cn/

Declaration of interest’s statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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