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Research Article

Evolutionary Model and Simulation Research of Collaborative Innovation Network: A Case Study of Artificial Intelligence Industry

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Based on integrating the fundamental attribute and the unique property of the collaborative innovation network, this paper establishes a collaborative innovation network model of Artificial Intelligence industry through depicting external stimulus conversion progresses and behaviors of network heterogeneous agents. Heterogeneous agents are the network elements of the model which regards the stimulus response as the evolutionary mechanism. Tencent is one of the largest Internet integrated service providers and one of the Internet companies with the largest number of service users in China, which has also set its sights on the development of the AI industry. Taking Tencent's patent cooperation network in the field of Artificial Intelligence as an example and using system simulation method, we analyze the evolutionary law of the collaborative innovation network topology structure, the coupling evolution phenomenon of the knowledge and the network topology structure, distinct roles that agents play in the network, and relationship between the agents' openness and the knowledge flow efficiency. We find the phenomenon of small world emergence more than once through the evolution of collaborative innovation network, whose degrees and reasons are also distinctive. There exists coupling evolution between the technological knowledge and the network structure. The collaborative innovation network is always oriented towards competitive industries. The agents' openness has an essential influence on the lifting range of the technological knowledge. Strengthening the main position of enterprises in AI technological innovation and enhancing the degree of openness among heterogeneous agents are a powerful guarantee for improving the performance of collaborative innovation.

1. Introduction

In the research process of collaboration innovation, the nature of network and system is gradually discovered and identified. And it underlies the conversion from single, local, and sectional innovation form to new integrate, extensive, and networking innovative form. Collaborative innovation is a powerful embodiment, because it underlines multiple agents to achieve crossing-group, multiphase, multilevel, multifactor cooperation and coordination. Collaborative innovation underlines the effective division of labor, smooth role transformation, and the feasible knowledge transference among those heterogeneous innovation organizations or individuals in durance of cooperation, which also prompts the dynamic evolution of collaborative innovation network. At the same time, the diversity of collaborative innovation network in agents' roles, operating mechanisms, and network topology structures fosters the nonlinear development process of the network; thus, its evolution presents intricate and variable characteristics.

Ankrah [1] conducted in-depth discussions on the elements of the collaborative innovation system. After reviewing the relevant theories of school-enterprise collaborative innovation, he extracted five elements of collaborative innovation system: the cooperation motivation, organizational form, stage operation, influencing factors, and results output. The conceptual framework is constructed through five elements, and the mechanism of collaborative innovation operation is described. Brink T [2], Huang [3], and Ivascu L [4] focused on the way of enterprise-enterprise, enterprise-university, and other organizations' collaboration. Zhao SL [5] focused on a macroregional perspective of collaborative innovation

network of region, and he divided the nature of the regional cluster innovation organization into eight dimensions: organizational concepts, resource types, innovation types, etc. Then, the international collaborative level based on the global perspective generally includes the exploration of the collaborative innovation network model of multinational enterprises and local enterprises [6, 7]. All of the abovementioned researches from a single perspective cannot cover the complete evolutionary structure of collaborative innovation network. In addition, from a methodological point of view, Walsh JP [8] believes that the cooperative structure of collaborative innovation is the essential representation of its collaborative model, and the difference in collaborative model is rooted in the difference of cooperation agents. Brem A [9] demonstrates the operation of the three-helix collaborative model in local ecological innovation projects. In addition, the agents, structural model, and mechanism are the three major elements of the system. Guan J [10] relies on the coupling of knowledge network and collaborative network to explain the operation mechanism of differentiated knowledge of the progressive innovation process. Although these studies have explained the evolution mechanism of collaborative innovation networks from various angles, most of them are ignoring the ideas of qualitative research and lack of quantitative description methods.

In addition, the existing researches are not enough to research the evolution characteristics of collaborative innovation networks, and to some extent the existing researches ignore the fundamental driving force for the formation and development of collaborative innovation networks. That is, the innovation agent interacts with the external environment to make microbehavioral decisions and promote capacity transitions, attribute improvements, and trait evolution of macronetworks [11–14].

Therefore, to fill these research gaps, taking collaborative innovation network of the Artificial Intelligence industry as an example, this paper collects the time series data related to network development and observes the changes of data through the network evolution process. Based on the research paradigm of cluster innovation network evolution process [15], it explores the basics attributes and unique characteristics of collaborative innovation network, according to which the three-helical model of collaborative innovation is further refined, and a model for collaborative innovation networks based on the evolutionary mechanism of the stimulus-response mechanism and heterogeneity being the main element of network is constructed. At the same time in researching method, the combination of complex network analysis methods and system simulation methods quantitatively describes the formation and development process of collaborative innovation networks, the evolution of network topology, and the transformation of the role of heterogeneous agents. In addition, the paper focuses on the coupling development of the knowledge elements and network topology structure of the collaborative innovation network at the stage of technology development and the relationship between the degree of openness of collaborative innovation agents and the efficiency of knowledge flow.

2. Theoretical Model

In order to provide the basic framework of collaborative innovation network evolution, explore its basic properties and unique characteristics in the process of evolution, and provide empirical evidence for the model simulation results, this paper uses data about Artificial Intelligence industry to model a collaborative innovation network at specific stages in a particular way. Based on the establishment of the initial theory, the relevant mechanisms of the cluster innovation network are introduced, and the general collaborative innovation network evolution model with universal significance is finally formed.

2.1. Basic Case. Tencent's patent cooperation network in the field of Artificial Intelligence was selected as a case study sample of the paper. In the aspect of data representation, since collaborative innovation, cooperative R&D, and other actions are difficult to be measured and evaluated, they can only be measured from the perspective of the output of cooperative innovation. In related research about the field of knowledge, patents or papers are recognized as the basis for measuring knowledge output. However, enterprises are the most important subject in collaborative innovation. Considering the limitations of the output papers in company and the superiority of patent data in information richness (applicants, application time, open time, IPC classification, etc.) and accessibility, this paper is ultimately based on Zhang G's [16] research to replace the collaborative innovation network with the industry-university-research patent cooperation network in AI industry and uses the patent application volume of AI industry as an innovation effect index or knowledge performance index to verify the evolutionary process of the collaborative innovation network.

Because one of the main goals of collaborative innovation is the fostering of technology, the industries that focus on the initial stage of technology have the greatest possibility in digging the most essential level of the collaborative innovation network and its evolutionary model, so the empirical analysis will be focused on industries that are in the "eruption" stage of technology. Global Artificial Intelligence Patent Resource Development Overview pointed out that the Artificial Intelligence industry emerged at the end of the 1990s and early 2000s, and the number of global patent applications in this field crossed the inflection point in 2011, showing explosive growth. This kind of phenomenon indicates that the AI industry is in the stage of its technical blowout and it can excavate and fit the typical process of collaborative innovation. Moreover, the field of Artificial Intelligence is a highly innovative industry. The application and publication of patents can largely represent the effect of innovation. The development process of the industry patent cooperation network can also represent the whole process of technological innovation and the development of industry collaborative innovation. In addition, the number of patents in China and the United States exceed more than 80% of global numbers in Artificial Intelligence area. These two countries undoubtedly become the dual-core driving engine in this field. Therefore, taking China's patent in the AI field as a sample and analyzing

its sample composition can expose the course of innovation and development of the AI industry to a large extent. At the same time, Tencent Technology (Shenzhen) Co., Ltd., published the largest number of patents in China's existing AI Big Three (Baidu, Alibaba, and Tencent), ranked third in the AI industry's global patent rankings, and the distribution of patent technology is more concentrated. The development process of Tencent in the field of Artificial Intelligence can represent the technological development trend of the Chinese AI industry to a great extent and it can also represent the evolutionary trend of the patent cooperation network. Therefore, for all of the abovementioned reasons, the paper selected the emerging AI industry as a sample and selected Tencent, one of the giants of AI industry, as the main target of data collection and plotted the evolutionary trend of the patent cooperation network according to data collection.

Due to the "local effect" of patent applications, this paper selected China's State Intellectual Property Office as a source of patent data. At the same time, Tencent's patents issued in the Artificial Intelligence industry are almost distributed in the two areas of G06 (computational calculation technique) and H04 (electric communication technology). Therefore, the applicant and the IPC Classification integrated retrieval method are used to search for all patents whose applicants contain "Tencent" and patents whose IPC classification number is "G06 OR H04." Considering the time lag of publication days, the application date is used as a time scale to depict the trend of number of patent applications. Finally, the result can represent the technology life cycle of China Artificial Intelligence technology in its current state.

Then, retrieve all patents whose applicants contain "Tencent and University" and whose IPC classification number is "G06 OR H04," and the applicant includes "Tencent and (Research Institute)" and the IPC classification number is "G06 OR H04." The application date is also used as a time scale to depict the trend chart of number of patent applications, representing the trend of cooperation between companies and heterogeneous institutions.

2.2. Specific Evolutionary Process of Collaborative Innovation Network. In general, there are delays of two years or more between the application date and the publication date. But according to analysis of past patent data (patent data of high-speed rail technology, patent data of aeroengine manufacturing technology, etc.), the delay between the application date and the publication date of its technology is usually up to 3-4 years in the emerging period of the high-tech industry. This may be due to gaining competitive advantage, possessing technical barriers, and the industry's giants having highly technical confidentiality in the emerging stage of the industry, etc. The Artificial Intelligence industry is a high-tech industry and it is currently in its high-speed development period. Therefore, some of its patent applications from 2014 to 2017 have not been disclosed yet, and data is largely missing. Tencent's first Artificial Intelligence patent technology application year can be traced back to 2001. Therefore, in order to reflect the development of the patented technology of the Artificial Intelligence industry more accurately, the paper selected the patent application data of the Tencent's Artificial Intelligence from 2001 to 2013 and plotted Figures 1 and 2.

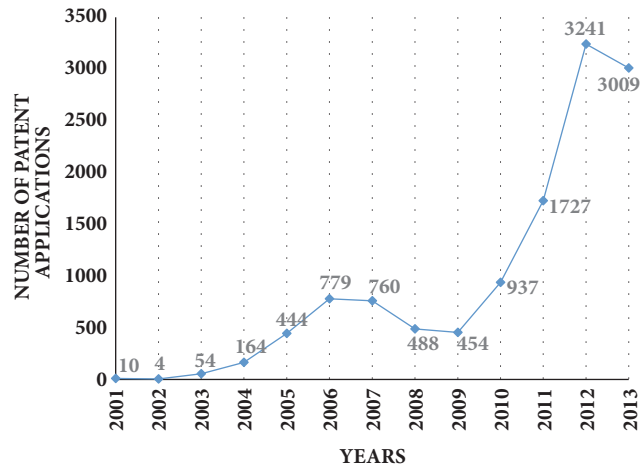

Figure 1: The number of Tencent's patent applications in AI technology from 2001 to 2013.

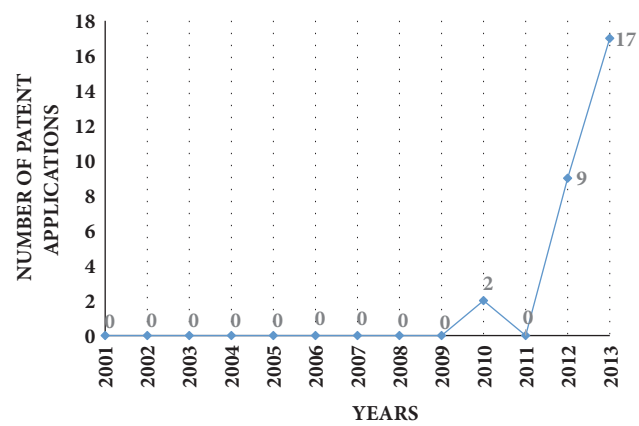

Figure 2: The number of Tencent's patent applications that Tencent cooperates with heterogeneous institutions in AI technology from 2001 to 2013.

Figure 1 shows the patent output tend of Tencent in Artificial Intelligence industry. It is seen that the trend of the entire patent output has undergone two ups and downs. According to this trend, we can regard the trough of patent output (2009) as a node; this node divides the entire development course into two stages (2001-2009, 2009-2013). Each phase is represented by an ups and downs process. The first stage was the period of rising output from 2001 to 2006, and the first peak of output was 779 in 2006. After that, the number of patent outputs showed a declining trend and fell to the bottom in 2009. In the second stage, the number of patent outputs increased rapidly since 2010, and the rate of increase became higher and faster. It has reached a peak of 3,241 by 2012. Comparing two stages, it can be concluded that the number of patents in the first stage has grown more slowly and the second stage shows us an explosive growth. Moreover, the number of patents in the latter period is much more than the former. Overall, Figure 1

shows that although the Artificial Intelligence technology has been developed at the initial stage, it has been slow and has experienced a bottleneck in technology development (2009). After overcoming this bottleneck, it has ushered in its own prime time of development.

Figure 2 shows Tencent's trends in number of patents for cooperation with heterogeneous institutions such as universities and research institutes. Compared with Figure 1, the trend and connotation shown in this figure are relatively simple; from 2001 to 2009, Tencent had no patent cooperation with universities and research institutes, and the cooperation output was zero. Noncorporate heterogeneous entities were first incorporated into the process of technological innovation in the Artificial Intelligence industry until 2009. After experiencing minor fluctuations, the amount of cooperation has been on a rapid upward trend. All of these indicate that the collaborative innovation between the enterprise and the university is gradually formed when the Artificial Intelligence technology has developed to a certain stage. With the passing of time and the development of technology, the degree of this heterogeneous cooperation becomes continuously deep and the number becomes continuously strengthened.

Therefore, it can be demonstrated in Figures 1 and 2 that Artificial Intelligence technology has experienced a slow process from the time of germination to the first peak of development. During this period, the output of new technologies shows a trend of flat growth. Without the participation of heterogeneous innovation partners, it is mainly the cooperation of internal company or between companies that provides support for technological innovation (2001-2006). Then, homogenous technical knowledge between companies begins to be redundant and the number of patents continues to decline. It hits the bottleneck of development in this field (2006-2009). At this time, in order to seek technological breakthroughs and introduce fresh sources of knowledge, companies began to establish collaborative and innovative relationships with universities and institutions that have strong technical capabilities. The emergence and continuous deepening of collaborative innovation also helped the company to break through technical bottlenecks, and knowledge performance and innovation achievements have been greatly developed (2009-2013).

From now on, the development process of collaborative innovation patent cooperation network in the current Artificial Intelligence field can initially obtain the unique characteristics of the evolution of collaborative innovation networks: heterogeneous partner selection and establishment of cooperation. In the process of evolution, the redundancy and communication of the knowledge elements interact with the evolution of the network structure, presenting a situation of coupling evolution, and the change of the subjective elements' effect has a significant impact on innovation. By analyzing Tencent's patent applications in the area of Artificial Intelligence, we verified the behavior rules and rule of role transformation of heterogeneous entities in the evolution of collaborative innovation networks and the impact of these laws on innovation performance or knowledge performance. It confirms the scientific nature of the paper's core theory, model assumptions, and simulation principles.

2.3. Collaborative Innovation Network Evolution Conceptual Model of AI Industry. Tencent's empirical data in the field of Artificial Intelligence and the analysis of specific networks above provide a preliminary development theory of collaborative innovation network. But it does not have wide applicability and must be further explored on the basis of specific collaborative innovation networks, using a broad reference to achieve the generalization of a specific model.

The literature research by [17], Tidd [18], Porter [19], Cooke [20], and Jos'e I. Santos [21] et al. shows that the theory of collaborative innovation has experienced a development process from shallow to deep and from point to point, from the collaborative research that is limited to the innovation elements within the enterprise to the interfirm collaborative innovation system based on the industrial chain division and cooperation (industrial cluster innovation), and then to the breakthrough of conceptual boundary of "enterprise as the agents, the academic institutions, governments, and financial institutions are all auxiliary and paying equal attention to the heterogeneous role of various innovation agents, and, finally, forming a regional network innovation pattern centered on industry, study, and research. That is to say, collaborative innovation is developed from the innovation of industrial clusters, but, compared with the cluster innovation network, the collaborative innovation network has a clearer level of difference in terms of the types of knowledge information.

The collaborative innovation network and the industrial cluster innovation network come down in one continuous line. Therefore, the collaborative innovation network inherits the basic attributes of the cluster innovation network evolution, that is, the knowledge network attribute derived from the specific case analysis and combined with the cluster innovation network theory; it can be transformed into a network. In essence, it is a knowledge information network. Learning of knowledge exchange is the root cause of network evolution. Network innovation agents make corresponding cooperative decisions based on their own knowledge characteristics and external environment changes (including cooperation and partner selection) [22–24]; this is the direct power of network (scale, structure) evolution. Therefore, the cluster innovation network is a typical self-organizing evolution network and has a complex topology structure. The innovation agents obtain the ability to cope with external environmental stimulus by constantly modifying the innovation activities and exhibit obvious small world network characteristics in the evolution process (short average path, high aggregation degree, and high heterogeneity distribution) [25]. However, the unique characteristics of the collaborative innovation network have also led to the different aspects of the cluster innovation network; that is, the information and roles continue to evolve with the evolution of the network, and the lack of research on the existing cluster innovation network model is the powerful manifestation of heterogeneous multirole.

So far, according to the complex adaptive principle and the basic attributes of the development of innovative networks, the stimulus-response mechanism can be regarded as the main mechanism for the evolution of collaborative innovation networks; that is, the change of the network is

the macroscopic manifestation of many micronetwork nodes responding to the stimulus [26]. In order to show the development of the level of innovation agents and the evolution of information more intuitively, this paper draws on the idea of three-helix model of industry, education, and research that highlights the evolution of role position. At the same time, in order to simplify research, on the basis of focusing on the most critical heterogeneous agents between enterprises and universities, a collaborative innovation network evolution model based on Artificial Intelligence industry is constructed, as shown in Figure 3.

The model combines the external environmental stimulus and agent response to AI new technology life cycle. Zhang G will regard the external environmental stimulus in the process of innovation network development as the emergence of new technology and bring about the unknown of technical knowledge. Zhang G [27] regards the external environmental stimulus in the process of innovation network development as the emergence of new technology bringing about the unknown of technical knowledge. However, the emergence of new technologies in reality is not only a technical stimulus, from the rise of Apple's leading smartphones to the gradual innovation process of Tencent WeChat and the research of the technology life cycle by many scholars; the successful technological innovations generally experience three stages of technology budding, technology incubation, and marketization [28].

In the budding stage of technology, the identification of potential market demand by enterprises is the key process at this stage. Market stimulus is the main type of stimulus. The stress agent is the enterprises directly in the market competition. They seek cooperation with each other to obtain more complete market information, and the more sensitive the market-capable enterprises to the emergence and change of market demand, the stronger the desire to cooperate and communicate between enterprises; the next technology incubation stage is the main process of the new technology from germination to maturity. The strong enterprises in the incubation stage of technology form the conceptual design of new products based on the preliminary judgment of market demand, and technology realization becomes the primary goal after conceptual design. At this time, the technical stimulus has become the main type of stimulus, and the original market-based enterprises have begun to seek technical partners under the influence of stimulus.

Levine's [29] research proved that the similarity and complementarity of technical knowledge in innovation clusters are a key factor in the choice of technology partners. If the similarity is too high, there is no need for cooperation. If the complementarity is too strong, the basis of cooperation will be lost. In the early stage of new technology incubation, technical knowledge is difficult to understand and learn, and enterprises with high knowledge similarity will strengthen cooperation to reduce the difficulty of technology learning; after that, knowledge redundancy will increase, and technical bottlenecks will appear. In the middle and late stages of technology incubation, universities with strong complementary knowledge began to join in cooperation, thus overcoming technical difficulties, and the level of new product technology is constantly maturing.

Finally, in the process of new technology marketization, stimulating source return to the market, enterprises actively establish cooperation with many enterprises in the industrial chain and supply chain under the pressure of new product marketing and coordinate agents to revert to the enterprise-enterprise [30], and thus the collaborative innovation network has completed an evolutionary cycle.

3. Statistics of Network Topology Structure

3.1. Degree and Degree Distribution. Degree is the most important indicator that describes the nature of a single node in a network. The degree of a node refers to the number of edges associated with the node and the number of points that the node directly connects. In most cases, the degrees of nodes in the network are not the same, so the distribution of degrees is used to represent the distribution of node degrees in the network. The function of degree distribution is generally recorded as $p(k)$, which reflects the statistical characteristics of all nodes of the network and is a macrostatistic.

3.2. Average Path Length. The length of the path between two nodes i, j in the network is defined as the number of edges of the shortest path connecting two points, denoted as $d_{i,j}$. The average path length of the network (denoted as L) is to average the shortest path of any pair of nodes, which is

$$L = \frac{1}{N(N-1)} \sum_{i \neq j} d_{i,j} \quad (N \text{ is the number of network nodes}). \tag{1}$$

The average path length is an important indicator to describe the cooperation between the cohesive subgroups. The more the "cross-distance" connections, the more the "shortcuts" that the network has, and the average shortest path of the network will be greatly reduced.

3.3. Average Clustering Coefficient. Aggregation coefficient is a parameter that is typically used to describe the clustering condition of network nodes, which reflects the degree of cooperation of "neighbor node" in the network, specifically, the connection between nodes directly connected to a certain node. Suppose node i is connected to other m nodes. There are at most $m(m-1)/2$ edges in the m nodes, and the actual number of edges is e; then, the actual subnets formed by the m nodes are defined. The ratio of the number of edges e to all the possible number of edges $m(m-1)/2$ is the clustering coefficient of node i, denoted as C_i, which is

$$C_i = \frac{2e}{m(m-1)}. \tag{2}$$

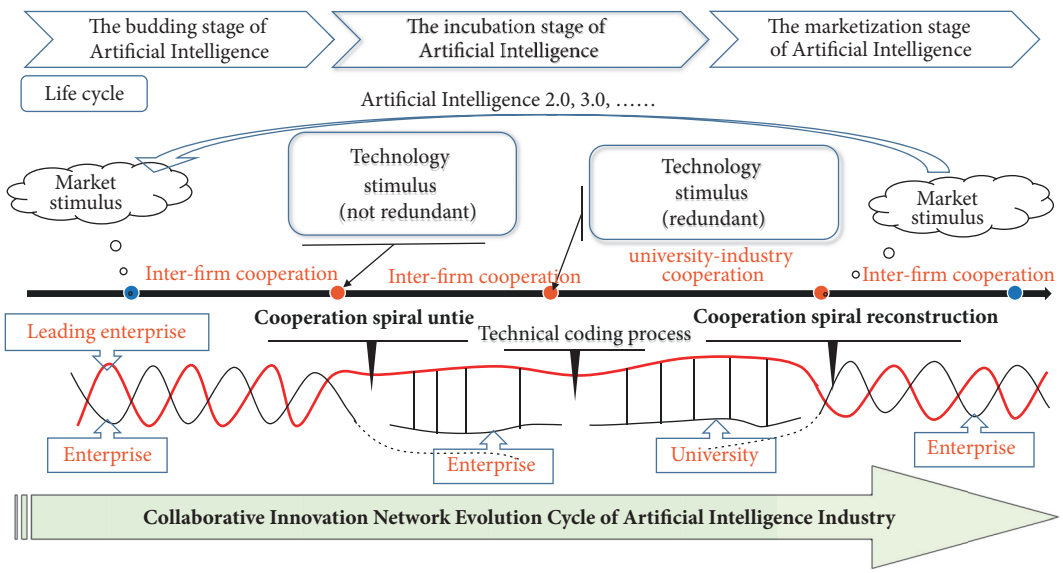

Figure 3: Collaborative innovation network evolution conceptual model of AI industry.

The average clustering coefficient of network is recorded as C; then

$$C = \frac{1}{N}\sum_{i=1}^{N} C_i \quad (N \text{ is the number of network nodes}). \quad (3)$$

3.4. Small World Quotient. After Watts [31] discovered the first small-world phenomenon of complex networks for the first time, a large number of scholars studied a variety of complex networks that existed in reality. Finally, they determined the overall connectivity and clustering features of the network by using the indicator of small-world quotient.

Usually, the parameters of topology structure of the actual network are compared with the parameters of topology structure of the random network. The ratio of them is defined as small-world quotient. The actual network and the random network have the same scale. In order to distinguish the following, the paper here refers to it as a relatively small-world quotient (denoted as RSW). Humphries [32] and Davis [33] et al. proposed its definition as

$$RSW = \frac{C_{actual}}{L_{actual}} \div \frac{C_{random}}{L_{random}}. \quad (4)$$

The model established in this paper follows the evolutionary strategy of network equilibrium but the scale of the network has not changed. Therefore, the ratio of the clustering coefficient and the path length of the actual network is directly used to represent the occurrence of the small-world phenomenon, which is

$$SW = \frac{C_{actual}}{L_{actual}}. \quad (5)$$

3.5. Overall Technical Knowledge Level of the Network. The overall technical knowledge level of the network is the sum of the total technical knowledge level k_i of each agent, which is

$$ksum = \sum_{i=1}^{N} k_i \quad (N \text{ is the number of network nodes}). \quad (6)$$

4. Model Simulation

4.1. Agents Heterogeneity. Referring to Valk [34] and Hermans [15], collaborative innovation network is assumed to be composed of nodes and links. The nodes represent differentiated innovative individuals or organizations, namely, agents. The links are regarded as collaborative relationships, specifically cooperative behaviors and information transference among these agents. Different roles of network agents on innovation process in collaboration network, as a kind of knowledge network, naturally are differences in information or knowledge retained by agents, including knowledge categories, knowledge levels, and ability to acquire new knowledge.

Drawing on the study of Bao [35], the paper applies dichotomy to describe heterogeneous information or knowledge held by network agents. We assume the number of innovation agents in collaboration network is $\boldsymbol{N}$. Agents' marketing information cognition levels are delegated by a row vector $\boldsymbol{S}$ with 20 dimensions while technology knowledge cognition levels are depicted by another row vector $\boldsymbol{K}$ with 20 dimensions. Then, select 80% agents as industries subjects in innovation process, and set up the remaining as education institution subjects. In general, industries master marketing information in quality and quantity better than mastering technology knowledge. As a result, each of the dimension factors x_s contained in the marketing information row vector $\boldsymbol{S}$ cognized by industries is assumed to randomly range in (0.3,1] in initial time, while each of the dimension factors x_k contained in the technology knowledge row vector $\boldsymbol{K}$

cognized by industries is assumed to randomly range in $[0, 1]$ in initial time. Besides, collaborative innovation network derives from industry-clustering innovation network and section innovation theory, which results in high-level homogeneity of those network industry subjects, so we set the first 15 dimensions of the vector for all industries to have the same value. The remaining agents represent colleges and universities in the network. Because universities usually lack market information, we set their cognitive vectors to randomly take values in each dimension of the initial time within the range of $[0, 0.3]$. Universities must have greater advantages and heterogeneity in technical knowledge, so its cognitive vector of technical knowledge is randomly chosen in the range of (0.8,1] for each dimension element in initial time.

According to Cowan [36], the overall knowledge level of market information for agent i is S_i, and the weight of each knowledge dimension is recorded as ω:

$$S_i = \sum_{s=1}^{20} \omega x_{s,i}. \tag{7}$$

The overall cognitive level of the technical knowledge for agent i is K_i, and the weight of each knowledge dimension is μ:

$$K_i = \sum_{k=1}^{20} \mu x_{k,i}. \tag{8}$$

The weight coefficients ω and μ are random values, and the sum of each coefficient is one.

4.2. The Evolution of Collaborative Innovation Network. With reference to Watts [31], the initial state of the network is set to be a regular network and follows the strategy of balanced evolution of network; that is, each step length only adds or deletes the edges of the network and does not change the attributes of nodes and edges, and the overall number of network edges does not change as well. The whole process of setting the evolution of the network in the system always maintains the state of full connectivity, and there is at most one connection between two nodes.

The Budding Stage of Technology. At the stage when market demand is found and gradually mature, individuals with higher levels of mastery of new market information will respond more sensitively to market stimuli and tend to change their relationship easily to seek more accurate and complete market information. Therefore, the probability of resetting the cooperation relationship of individual i is defined as P_i, and the higher the knowledge level of market information S_i is, the greater P_i is. In addition, as the network evolves, the agent's knowledge level S_i will change under the effect of interactive learning, and P_i will also change with time, considering the continuity of the agent's willingness to change. Therefore, it is assumed that the resetting probability of an individual's partnership in the period of $\boldsymbol{t}$ is a function of its current knowledge level and the probability of resetting the previous partnership. In order to prevent the network from being evolved too quickly, the probability of initial network relationship change in this paper is set to $P_0 = 0.05$. Therefore,

$$P_0 = 0.05 \tag{9}$$

$$P_{i,t} = \min\left\{P_{i,t-1} \exp\left(2S_{i,t} - 1\right), 1\right\}. \tag{10}$$

Let node j directly connected to node i be a first-level node of i, a set of j be denoted by $First(i)$, a node k connected by a node from node i (excluding the node in $First(i)$) be a second-level node of i, and a set of k be marked as $Second(i)$. In this stage, the flow information between networks is mainly based on market demand information. Then, according to the two principles of relationship change strategy, namely, availability of channels and reliability of capabilities, the relationship change rules of network node can be set as follows: node i in the period of $\boldsymbol{t}$ disconnects i with the node $jmin$ which has the smallest market information awareness level $S_{j,t}$ in the set $First(i)$ with probability $P_{i,t}$, and the connection between i and the node $kmax$ which has the highest knowledge level of market information $S_{k,t}$ in the set $Second(i)$ is added.

In addition, the degree of individual openness will affect the efficiency of cooperation between network nodes. Therefore, the two agents i and $kmax$ that are newly established to collaborate learn from each other with probability β (market knowledge). The higher the degree of individual openness is, the greater β is. That is, i and $kmax$ convert the elements in cognitive row vector of its own market to the highest of the two with probability β, and $S_{i,t}$ evolves to $S_{i,t+1}$ and $S_{kmax,t}$ evolves to $S_{kmax,t+1}$. Then, the abovementioned operation is repeated several times until the network indicators tend to converge.

The Incubation Stage of Technology. At the beginning of this stage, the powerful agents who mastered a large number of market demands for innovation began to seek technical cooperation so that the conceptual design of the product could be technically realized. The mainly influencing factors of changing relationship of the agent include the strength of market power and the degree of mastery of market information. When strong market players have strong technical capabilities, in order to maintain their competitive advantage, the agent has a higher degree of mastery of new technology knowledge and is more inclined to maintain the existing network structure. Similar to the budding stage of technology, S_i, K_i, and P_i will change with time. Taking into account the continuity of the agent's willingness to change, we suppose that the relationship of the resettlement probability P_i of individual i in the $\boldsymbol{t\text{-}th}$ period is its current knowledge level (including market knowledge and the two kinds of technical knowledge) and the previous function of resetting the probability of cooperation relationship. Then,

$$P_0 = 0.05 \tag{11}$$

$$P_{i,t} = \min\left\{P_{i,t-1} \exp\left(S_{i,t} - K_{i,t}\right), 1\right\}. \tag{12}$$

The addition of technical knowledge and its unique characteristics have led to corresponding changes in the

rules of change in network partnerships. The similarity and complementarity of technical knowledge are the basis of network connection between innovation agents. If the similarity is too strong, there is no need for cooperation. If the complementarity is too large, the basis of cooperation will be lost. Let the technology gap of node i, j be

$$\delta_{ij} = \sum_{k=1}^{20} \left(x_{k,i} - x_{k,j}\right)^2. \tag{13}$$

The higher δ_{ij} is, the stronger the complementarity of technical knowledge between i, j is. The lower δ_{ij} is, the stronger the similarity of technical knowledge between i, j is.

Therefore, we set change rule of the network node's cooperative relationship as follows: Node i disconnects the connection between i and the node *jmin* with the probability $P_{i,t}$ in the ***t-th*** period. The node *jmin* has the lowest knowledge level $K_{j,t}$ and it is also in the set $First(i)$. The connection is added between the node i and *Kmiddle* whose technology gap $\delta_{ik,t}$ is at the middle level (when there are even nodes in $Second(i)$, $\delta_{ik,t}$ is arranged from small to large, taking the ***(n-1)/2th*** node; when there are an odd number of nodes in $Second(i)$, $\delta_{ik,t}$ is arranged from small to large, taking the ***n/2th*** node) in the set $Second(i)$. The two agents i and *Kmiddle* that newly establish cooperation also learn from each other with probability β (technical knowledge) and then repeat the abovementioned operations until the network indicators tend to converge. In this process, the convergence of technical knowledge among network agents eventually encounters technical bottlenecks. In order to find more useful information, after the convergence of network indicators, the disconnection principle of node i and its cooperation relationship remain unchanged, but the principle of connection of cooperation relationships changes to add the connection between node i and node *kmax* with the largest technical gap in the set $Second(i)$, and they learn from each other with probability β (technical knowledge). Then, repeat the operation several times until the network indicators tend to converge.

The Stage of Marketization. After the incubation stage of technology, the network technology level continues to increase until the new technology matures and the new technology marketization phase begins. The outside world mainly stimulates the market again; the more the network agent has complete technology, the more actively it will look for marketing channels, and the more inclined it will be to find new partners. Therefore, similar to the abovementioned principle, it can be assumed that

$$P_0 = 0.05 \tag{14}$$

$$P_{i,t} = \min\left\{P_{i,t-1} \exp\left(2K_{i,t} - 1\right), 1\right\}. \tag{15}$$

The flow of network information is based on market information at this stage again, and the technical knowledge does not have a great impact on the establishment of cooperation anymore, so the changing relationship strategies of the stage of marketization and the first stage are the same and will not be described again. Repeat the operations several times so that the network indicators tend to stabilize.

5. Simulation Results

The abovementioned research shows the three stages of the evolution of collaborative innovation networks. The incubation stage of technology reflects not only the process of cooperation of heterogeneous agents, but also the main stage for the improvement of the overall technological innovation capability of the cluster. At this stage, the evolution of network structure and the exchange of information knowledge are the most complex. At the same time, due to space limitations, this paper only selects the incubation stage of technology to carry out simulation results and conclusions.

Assume that there are 100 innovation agents (n=100) in the collaborative innovation cluster, each agent is connected with four agents adjacent to each other; that is, the degree of each node at the initial time is 4, and then the attributes and interaction behaviors of the agent are set according to the model, and the agent learning probability is set to 0.7. The results of several tests show that as time increases, the network's various measurement and comprehensive knowledge levels tend to converge, and the observation time does not need to be too long. The termination rule of the evolution of the network cycle in Gulati's [37] study also confirms this. Therefore, based on the experimental results, the observation period from the beginning of technology incubation to the technical bottleneck is set to 100, the observation period from the technical bottleneck to the mature technology is set to 100, and the total observation duration is t=200. In order to eliminate single-shot errors as much as possible, 10 independent simulation operations are repeated. Figures 4, 5, 6, and 7 and Table 1 are the average of 10 simulation results.

5.1. Evolution of Basic Topology Structure of Collaborative Innovation Network. The small-world quotient comprehensively reflects the degree of closeness and connectivity of the network. From its overall trend, it can be seen that collaborative innovation network evolves, as shown in Figure 4. The small-world quotient is affected by two factors, the fluctuation is large, and the image noise is greater. In order to grasp the global change more clearly, Figure 4 is the result of moving average of the original data.

As shown in Figure 4, in the early stage of technology incubation of the collaborative innovation network, the small-world Q of the network first grows slightly and briefly and reaches the peak of growth at around t=10 and then begins to decline rapidly; at t=40 it drops to the bottom of the valley and maintains a low level of stability during the 40-90 period; in the later stage of technology incubation, t=100 and t=120 are the main turning points. In these 20 steps, the small-world Q of the network rises and exceeds the first peak rapidly. After the 120th phase of the evolution, the small-world quotient has risen at a slower rate and has stabilized at about the 150th phase but has remained at a higher level.

The small-world Q only shows the general changes of the collaborative innovation network. To explore its specific motivation of change and more detailed evolution of the network topology structure, it is necessary to combine the two determinants of the small-world Q: the average path

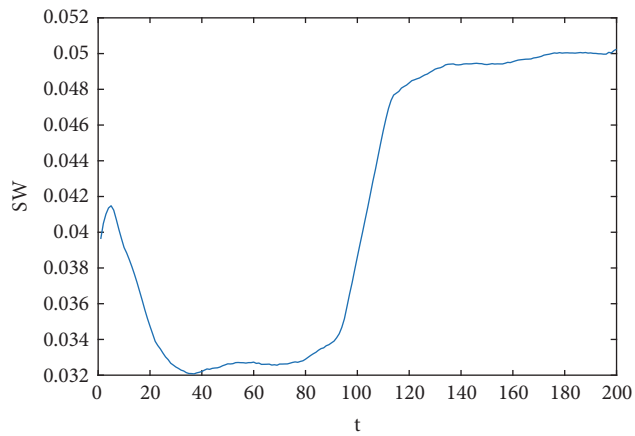

Figure 4: The evolution picture of the collaborative innovation network small-world Q.

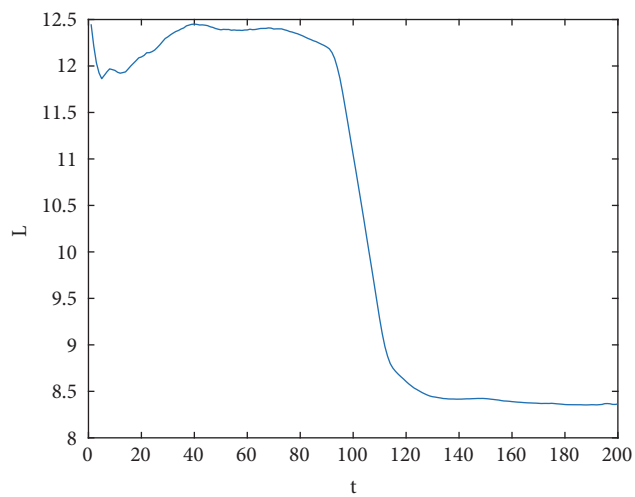

Figure 5: The evolution picture of the collaborative innovation network average path length.

length of network and average clustering coefficient. Therefore, according to the key points of the evolution of the collaborative innovation network obtained in Figure 4, this paper lists the network topology parameters at four moments t = 10, 40, 100, and 150, as shown in Table 1.

It can be seen that the small-world Q experiences the first peak (t=10), the relatively small world Q is greater than 1, and the network has significant features of small-world network. The average path length of the network is at a medium level compared with other times. On the other hand, the average of the clustering coefficient of network is relatively high, which indicates that the cooperation between the innovation agent and its neighbors is still close in the collaborative innovation network. However, a few innovative agents begin to establish direct contact with the distant agents, which reduces the average path length of the network.

After that, the small-world Q drops to the bottom (t=40). At this time, the average clustering coefficient of the collaborative innovation network drops sharply, but the path length increases, indicating that the effectiveness of information dissemination in the small-world network is greatly reduced. The cooperation between the neighboring agents in network has become very sparse, and some key "remote cooperation" has gradually reduced.

This sluggish situation continued until the 100th phase. As the network agents began to actively seek cooperation with agents which have the higher technological content, the small-world features of the collaborative innovation network reappeared. The average network path length and average clustering coefficient were dramatically changed. By the 150th phase, the network average path length dropped sharply from 12.0371 in 100 phases to 8.4181, and the average clustering coefficient decreased from 0.4159 to 0.3900, but the small-world quotient increased significantly. Small-world Q is also greater than 1. During this period, although the closeness of the cooperation between the agents in the network has decreased, the cross-distance of cooperation has greatly increased. The innovation agent hopes to acquire more knowledge and improve its own technical level by acquiring the "structural hole" position or connecting heterogeneous nodes.

5.2. The Collaborative Evolution of Technical Knowledge and Network Topology Structure. The knowledge level of the collaborative innovation network directly determines the probability of cooperation change and the choice of cooperation. The establishment and disintegration of the cooperative relationship and the degree of individual openness in turn affect the change of knowledge level. In addition, the knowledge flows between the networks during the technology incubation period mainly based on technical knowledge. So in this period, there must be a certain coupling relationship between technical knowledge level and topology structure of collaborative innovation network.

Figures 5 and 6 reveal the evolution of the network's average path length and average clustering coefficient of the network during the incubation stage of technology in collaborative innovation network. Similar to the processing method of the small-world Q's image, the paper also performs moving average processing on the two sets of images. Figure 7 shows the trend of the overall technical knowledge level of the network with the evolution period t.

Based on these figures, it can be seen that the rising period of technical knowledge is a significant period of small-world (t=0-20, 100-140). The average path length of collaborative innovation networks in these periods is relatively short, while the degree of network clustering is relatively high. The "neighbor cooperation" and "remote cooperation" in the network are more active, and the effectiveness of network information transmission is very strong. Therefore, the efficiency of knowledge dissemination is extremely high, and the overall technical knowledge level of the network will be rapidly improved. At the same time, comparing the images of t=0-20 and t=100-140, we can see that the shorter the average path of network and the higher the degree of clustering (that is, the higher the small-world Q), the greater the improvement of technical knowledge and the faster the improvement.

Table 1: The network topology structure parameter values.

The network topology structure parameter	t=10		t=40		t=100		t=150	
	m	***std***	***m***	***std***	***m***	***std***	***m***	***std***
Average path length (***L***)	12.1199	1.3782	12.4769	1.4366	12.0371	1.0728	8.4181	1.8947
Average clustering coefficient (***C***)	0.4852	0.0249	0.3954	0.0326	0.4159	0.0338	0.3900	0.0267
Small-world Q (***SW***)	0.0406	0.0056	0.0320	0.0038	0.0348	0.0044	0.0494	0.0146
Relatively small-world Q (***RSW***)	3.3741	0.4667	2.6592	0.3133	2.8942	0.3640	4.1030	1.2131

Notes: ***m***(mean values)/***std***(standard deviation): repeat 10 times independent simulation operations to calculate the mean and standard deviation of all the parameters at the given time in the ten simulation results.According to the literature [33], the ***RSW*** calculation formula is $L_{random}=\ln(n)/\ln(k)$,$C_{random}=k/n$.

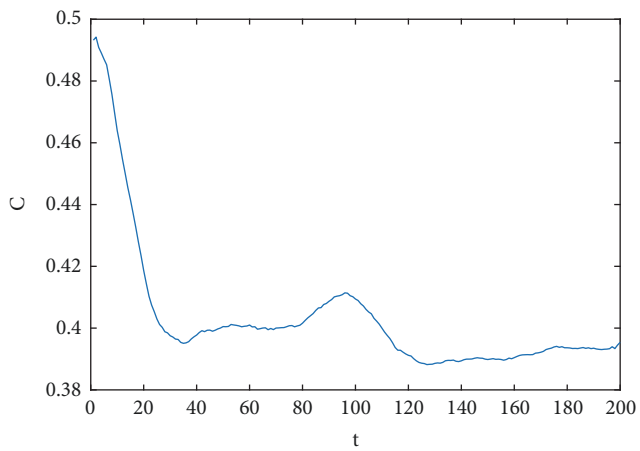

Figure 6: The evolution picture of the collaborative innovation network average clustering coefficient.

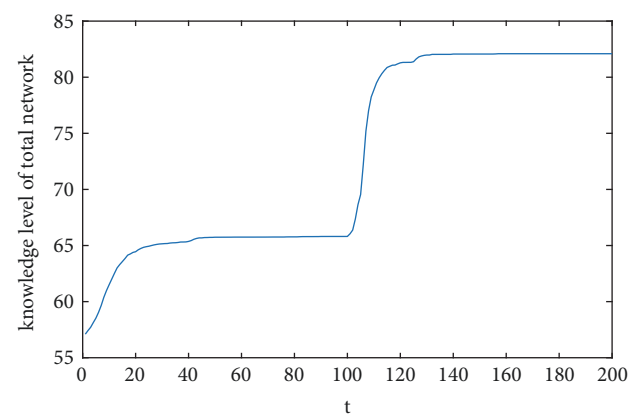

Figure 7: The evolution picture of the collaborative innovation network total technological knowledge level.

On the other hand, the characteristics of knowledge elements also affect the topology structure of the network. The continuous interaction of innovative agents leads to the improvement of the overall knowledge level of the cluster, which also leads to the emergence of redundant information. This trend is constantly increasing, which makes it difficult for the main agents to obtain useful information. The foundation of network cooperation is lost, cross-distance cooperation and the cooperation in the cohesive subgroup have become sparse.

In addition, the stronger the complementarity of flow knowledge of network, the more obvious the small-world structural characteristics of the network. For example, the period t=0-20 is the initial stage of technology incubation, the coding degree of technical knowledge is low, and the enterprises with stronger homogeneity are easier to cooperate. At this time, the similarity of network flow knowledge is higher, as shown in Figure 5. The average path length of the network is not significantly reduced, indicating that the amount of "remote cooperation" that occurs during the evolutionary process is small and disappears quickly. The technical knowledge with higher homogeneity will quickly become invalid and ineffective in the process of interactive flow of knowledge; thus, the small-world network speeds up its disintegration. In the t=100-140 period, due to the emergence of redundant information and technical bottlenecks, enterprises tend to seek technical support from universities, and the complementarity of flow knowledge of network has greatly improved. The average network path in Figure 5 has dropped significantly. At the same time, the networks clustering coefficient in Figure 6 has instead grown, and the structural characteristics of the small world are extremely significant because the flow of complementary knowledge requires more structural holes that connect different cohesive subgroups.

In summary, not only the change of network topology structure but also the coevolution law of collaborative innovation network and technical knowledge characteristics are explained from the perspective of knowledge elements.

5.3. The Influence of Agent Openness on the Efficiency of Flow of Technical Knowledge. On the basis of the above-mentioned research, this paper sets the learning probabilities after establishing the cooperative relationship between the innovation agents to 0.3, 0.5, and 0.7, respectively, and performs three independent simulation runs to obtain the evolutionary map of technical knowledge level (Figure 8). It can be seen that there is a certain relationship between the degree of individual openness and the efficiency of flow of technical knowledge: the greater the learning probability β, the greater the improvement in technical knowledge. That is, the openness of the individual has a positive impact on the improvement of technical knowledge, and the complementarity of technical knowledge has a positive regulation effect on this relationship, but there is no significant correlation between the learning probability β and the flow rate of technical knowledge.

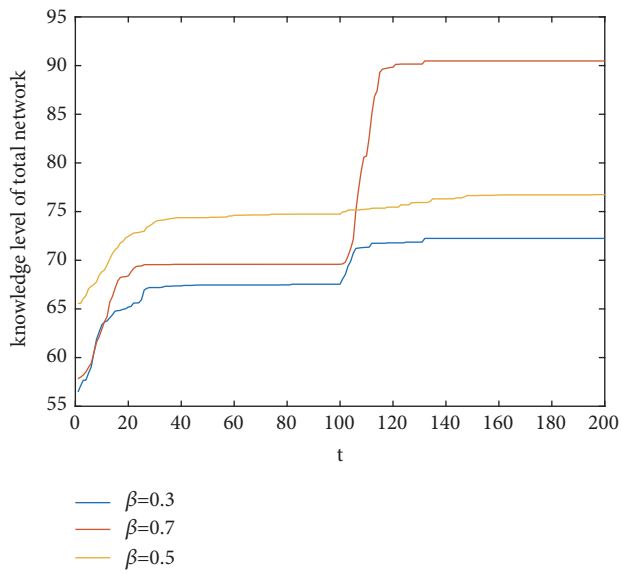

Figure 8: The evolution picture of the collaborative innovation network's total technological knowledge level under different values of β.

6. Conclusion

Collaborative innovation network is developed by cluster innovation network, which has a series of basic attributes of complex networks [38]. Firstly, it follows the principle of complex adaptation. The response to environmental stimuli is the fundamental driving force of network evolution, and the macrointegration of microindividual's decision-making behavior promotes the characteristics of its evolution. Secondly, the most essential feature of the collaborative innovation network is the heterogeneity of the cooperation agent. Based on the understanding of these two points, this paper takes Tencent's data in the field of Artificial Intelligence as a case and establishes a stage evolutionary model of collaborative innovation network by portraying external stimulus changes and heterogeneous agents' behavior of collaborative innovation network. The **MatLab** system simulation software is used to explore the dynamic evolutionary characteristics of collaborative innovation network topology structure in the technology incubation stage, the coevolution of technical knowledge and network structure, the degree distribution characteristics of network, and the influence of agent openness on the efficiency of technical knowledge flow. The conclusion is as follows.

The process of technology incubation can be divided into two stages. The incubation to the technical bottleneck is the first stage, and the technical bottleneck to the technical maturity is the second stage. The first stage is mainly the exchange and cooperation of technical knowledge among enterprises. The "remote cooperation" of network appears, but the amount of 'remote cooperation' is small and the duration of this kind of cooperation is fleeting. Then, the network is sparse and the technical bottleneck appears. In the second stage, universities begin to actively participate in cooperation. The "remote cooperation" of network emerges in abundance, the links within the cohesive subgroups also increase, the network information is fully exchanged, and the technology level of network continues to improve and mature. On the whole, although the whole process shows two small-world peaks, the degree of change is different, and the changes of network topology structure are not similar.

There is a cooperative evolution between technical knowledge and network topology structure. First of all, the two influence each other. The degree of coding of technical knowledge will affect the choice of the network partner, which can also affect the network structure. On the one hand, the small-world appearance of the network will promote the flow of technical knowledge; on the other hand, it will bring about the redundancy of knowledge and change the coding degree of knowledge. Secondly, the stronger the complementarity of mobile knowledge in network is, the more obvious the small-world feature of network is. Correspondingly, the more efficient the learning of knowledge of the network with strong small-world feature is, the more frequent and thorough the exchange of knowledge is.

The role of heterogeneous agents of collaborative innovation network is different. Groups of university are the supporters of technology, and the groups of enterprise are the recipients of technology. But no matter at which stage, the network leading is a strong enterprise with competitive advantages. Strengthening the leading position of the enterprise in innovation is a reasonable and correct policy direction.

There is a certain correlation between the learning efficiency of the agent and the flow efficiency of technical knowledge. The efficiency of agent's learning has a positive impact on the technical knowledge of the cluster, and the complementarity of technical knowledge has a positive effect of adjustment. However, the correlation between learning efficiency and the speed of technical knowledge is not obvious. Therefore, enterprises in the position of "structural hole" should actively strengthen their own development level and learning ability to improve the knowledge level and innovation performance of the cluster.

Data Availability

The simulation data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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