Structural Evolution Features of a Collaborative Innovation Network of College Students from the Perspective of Knowledge Flow

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Abstract—Knowledge exchange and transfer are very important in a R&D environment driven by knowledge and technology. This paper aims to study the structural evolution features of the Collaborative Innovation Network (CIN) of college students from the perspective of knowledge flow. The knowledge flow among the collaborative innovation relationships of college students has not only produced many innovation achievements and high innovation conversion values, but also promoted knowledge sharing and increased regional economic benefit. To figure out the structural evolution features of CIN from the perspective of knowledge flow, at first, this paper explores the network-shaped knowledge flow pattern, constructs a model that can reflect the innovators' citation of innovation knowledge and the interaction between related factors and their interaction space, and analyzes the distance attenuation of knowledge flow of CIN and its evolution trend. Then, this paper combines the structure of CIN with the evolutionary game, builds an Evolutionary Game (EG) model of CIN, and analyzes the evolution law of college students' collaborative innovation behavior in CIN. At last, this paper gives experimental results and verifies the validity of the proposed model.

Keywords—knowledge flow, collaborative innovation network (CIN), structural evolution feature, evolutionary game (EG)

1 Introduction

As market environment, technology environment and policy environment are becoming increasingly complex these days, it's very difficult for a single innovator to achieve high-level innovation and R&D [1–3]. Innovators can learn from each other through CIN to improve the conversion rate of their R&D achievements [4–8]. Knowledge exchange and transfer are very important in a R&D environment driven by knowledge and technology [9–12]. As the key to pushing scientific progress, the knowledge flow among the collaborative innovation relationships of college students has not only produced many innovation achievements and high innovation conversion values, but also promoted knowledge sharing and increased regional economic benefit [13–18]. Therefore, it's a meaningful work to analyze the CIN of college students from the perspective of knowledge flow.

Yang and Wang [19] discussed the influence of organizational social network on the collaborative innovation of enterprises, the intermediary role of knowledge sharing, and the regulatory role of digital construction. Based on theories of social exchange and social cognition, Miao et al. [20] built an integration model of organizational social network influencing enterprise collaborative innovation, adopted hierarchical regression analysis to sample high-tech enterprises in the Yangtze River Delta of China, and drew the conclusion that improving organizational social network and increasing the knowledge sharing behavior of employees can enhance the collaborative innovation ability of enterprises. Shi et al. [21] examined the role of knowledge sharing among member enterprises between collaborative innovation activities and innovation performance and between building information modeling application and innovation performance in the construction supply chain, then authors proposed a model to describe the relationship between collaborative innovation activities, building information modeling application, knowledge sharing and innovation performance in the construction supply chain, and verified the rationality of the model via empirical analysis. Olawale et al. [22] introduced a framework of Center of Collaborative Innovation (CCI) and described how the school of engineering collaborates with the school of business and department of arts and design to promote innovation-driven entrepreneurship across the university. Then, authors explained how CCI promotes innovative entrepreneurship by making use of the knowledge and resources of different units and disciplines in university and creating a synergistic force to promote experiential learning and innovation-driven entrepreneurship on campus. Shi [23] argues that knowledge flow is an explicit behavior of college students during their Cooperative Innovation Learning (CIL), in the paper, the author analyzed the multi-factor action mechanism of knowledge flow on CIL platforms for college students, explained the formation mechanism of CIL network, and measured model variables of the network; moreover, the paper analyzed the robustness of functions of the proposed network based on knowledge flow and gave multi-factor variable analysis results of the model. Wang and Hua [24] built a model of collaborative innovation based on gray system theory to figure out how the efficiency of innovation is affected by the structure of collaborative innovation network. Their findings show that when the degree of grayscale of knowledge flow is low, the optimistic collaborative innovation network structure is a random network characterized by low average path length; when the grayscale degree is medium, the optimistic collaborative innovation network structure is a small world network characterized by high small-world coefficient. At last, a few suggestions were proposed.

World scholars in related research fields have studied the CIN's features, evolution patterns, and influencing factors, however, still there are some problems pending for solutions. At first, the regional CIN is a dynamic open system that evolves over time, so the analysis of time series samples is a necessary work; second, research on sub-groups between individuals and the entire CIN is insufficient, and research on the evolution mechanism of the structure of CIN and its influencing factors needs to be deepened further. For these reasons, this paper studied the structural evolution features of CIN of college students from the perspective of knowledge flow. In the second chapter, this paper showed the network-shaped knowledge flow pattern, built a model to reflect the innovators' citation of innovation knowledge and the interaction between related factors and their interaction space, and analyzed the distance attenuation of knowledge flow of CIN and its evolution trend. In the third chapter, this paper combined the structure of CIN with EG, built an EG model for CIN, and analyzed the evolution law of college students' collaborative innovation behavior in CIN. At last, this paper gave experimental results and verified the validity of the proposed models.

2 Distance feature of knowledge flow in CIN

Figure 1 shows the network-shaped knowledge flow pattern. In fact, many factors can affect the knowledge flow in CIN. The flow of innovation knowledge usually exhibits two combined forms, and their manifestations in the action space are quite complicated under the influence of different factors.

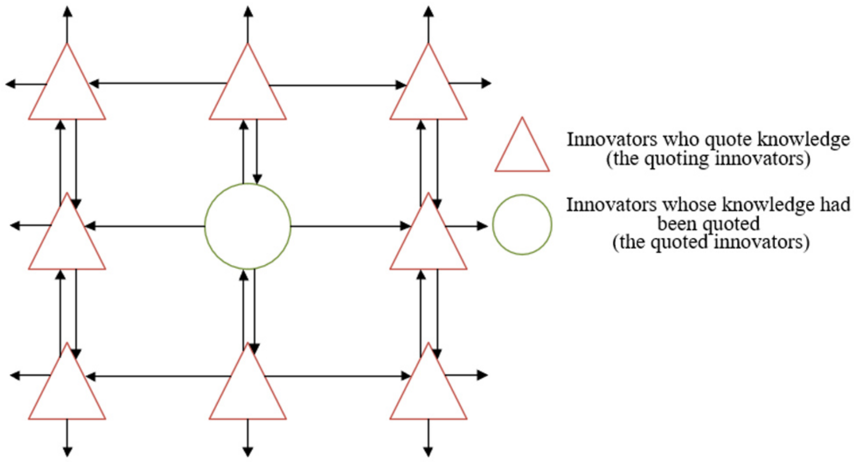

Fig. 1. The networked-shaped knowledge flow pattern

Distance attenuation of knowledge flow in CIN is an important spatial feature of CIN, it indicates that knowledge tends to flow between two innovators that are closer in the CIN. To reveal this distance attenuation feature of CIN, this paper built a model to show the realization process of knowledge flow in CIN and verify the weakening of this feature during knowledge flow in network.

In this paper, the standard of time series statistics was set as the time limit of sample data to analyze the distance attenuation feature of knowledge flow in CIN and its evolution trend, so as to reduce the influence on sample data cause by the truncation of time.

This paper built a model to reflect the innovators' citation of innovation knowledge and the interaction between related factors and their interaction space (hereinafter referred to as the "interaction model" for short), by default, this paper holds that the space of innovators' citation of innovation knowledge is under the joint action of factors including innovation targets (objective factor), quoted innovators (collaborative factor), and the difference between innovation targets of innovators. Assuming: D_{ij} represents the knowledge flow from innovator i to innovator j (namely the knowledge of innovator i is quoted by innovator j). According to the time limit of sample data, data of samples of 12 years from 2010 to 2022 were collected, denoted as D_{ij}; X_i represents factors that can affect innovator i (quoted innovator); Y_j represents factors that can affect innovator j (quoting innovator); G_{ij} represents the gap between j and i; ρ_{ij} represents noise, and it satisfies $P[\rho_{ij}|d_{ij}] = 0$. Based on these assumptions, the interaction model was built as follows:

$$D_{ij} = X_i + Y_j + G_{ij}(c_{ij}) + \rho_{ij};\ i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, m;\ i \neq j \tag{1}$$

The quoted innovator factor and innovation target factor can be linked to some attribute variables of the quoted innovator and the quoting innovator. Assuming the variables are represented by x_1 and x_2, β_1 and β_2 are parameters to be estimated, then the linking process is given by the following formulas:

$$X_i = X(x_i, \beta_1) = \beta_1 x_i;\ i = 1, 2, \ldots, m;\ Y_j = Y(y_j, \beta_2) = \beta_2 y_j;\ j = 1, 2, \ldots, m \tag{2}$$

Because the quotation of innovation knowledge peaks within half a year after the collaboration relationship of innovators is formed, and less than 50% of the quotation of innovation knowledge happens within one year after the collaboration relationship is formed, so in this paper, X_i is measured by the number of innovation knowledge of innovator i from year o–1 to year o (o = 2010, 2011, …, 2022), and Y_j is measured by the number of innovation knowledge quoted by innovator j in the current year; assuming $c_{ij}^{(1)}$ represents the innovation distance between the two innovators, $c_{ij}^{(2)}$ represents the innovation technology distance between the two innovators, then there is:

$$G_{ij} = G(x_{ij}, \gamma) = \sum_{l=1}^{L} \gamma_l c_{ij}^{(l)};\ i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, m;\ i \neq j \tag{3}$$

$c_{ij}^{(2)}$ can be calculated by the technology distance formula given below:

$$r_{ij} = \frac{\sum_{n=1}^{N} g_{im} g_{jm}}{\left(\sum_{m=1}^{m} g_{im}{}^2 \sum_{m=1}^{m} g_{im}{}^2 \right)^{1/2}};\ i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, m;\ i \neq j; n = 1, 2, \ldots, 36 \tag{4}$$

This paper performed second-level technology classification on innovation knowledge in the knowledge flow of CIN based on patent retrieval software USPTO and generated 40 technology categories. Assuming g_{in} and g_{jn} represent the ratios of the number of quoted knowledge of the n-th category to the total number of quoted knowledge of innovator i and innovator j. In addition, following the generation path of sample data, the innovation technology distance between innovators was calculated. Calculations of the quoted innovator adopted the data of innovation knowledge information from year o–1 to year o, while calculations of the quoting innovator adopted the data of innovation knowledge information of year o.

Formulas 1–3 were combined to transform the constructed model, then we have:

$$D_{ij} = \beta_1 x_i + \beta_2 y_j + \gamma_1 c_{ij}^{(1)} + \gamma_2 c_{ij}^{(2)} + v_{ij} \tag{5}$$

Because the discrete sample data of innovation knowledge does not conform to the normal distribution, using conventional least square method to estimate the constructed model may generate a large deviation, so this paper constructed a Poisson distribution variable shown as the following formula for the sample data of innovation knowledge to perform estimations based on the maximum likelihood method.

$$g\left[D_{ij} = d_{ij} \mid X_i, Y_j, G_{ij}\right] = \frac{e^{-\lambda_{ij}} \lambda_{ij}^{d_{ij}}}{d_{ij}!} \tag{6}$$

3 EG Model for CIN

3.1 Innovation investment

Figure 2 shows the EG model established for CIN. Under the combined effect of internal and external driving forces of technology innovation requirement and the pressure of enhancing innovation ability, innovators would form collaborative relationship and participate in collaborative innovation activities based on principles of innovation investment and benefit distribution, further, they would perform R&D collaboration and achievement transformation.

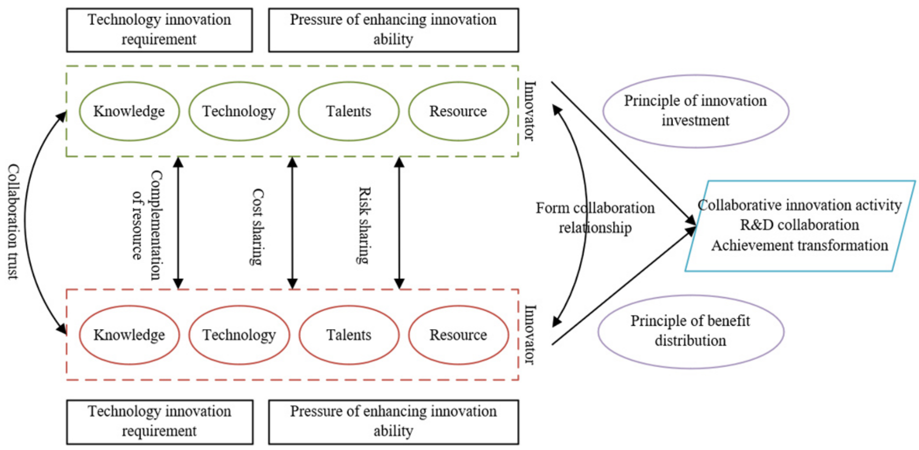

Fig. 2. The EG model for CIN

From the perspective of knowledge flow, in CIN, student innovators do not have enough ability to choose the best knowledge flow strategy that can maximize innovation benefit, they usually make their heuristic knowledge quotation decisions based on local information such as their innovation targets and requirements. This paper combined CIN with EG to construct an EG model for CIN to analyze the evolution law of the collaborative innovation behavior of college students in CIN.

The innovation investment principle of CIN requires that innovators must make innovation investment no matter they conduct collaborative innovation or not. This paper used early-stage innovation benefit and network node degree to measure the innovation investment of innovators during the process of collaborative innovation, the following formula gives the innovation investment of innovators in each collaborative relationship:

$$x_{a,\dot{b}}(o_m) = (1-q_1)\frac{e^{\beta \cdot n_{a,\dot{b}}(o_{m-1})}}{\sum_{i=0}^{l_a} e^{\beta \cdot n_{i,\dot{b}}(o_{m-1})}} + q_1 \frac{e^{\beta \cdot l_a}}{\sum_{i=0}^{l_a} e^{\beta \cdot l_i}} \tag{7}$$

$$\sum_{\dot{b}=0}^{l_a} x_{a,\dot{b}}(o_m) = D \tag{8}$$

The first term in Formula 7 is the indicator of innovation benefit, it's described by the standardized ratio of the innovation benefit of node *a* in collaboration relationship $\dot{b}$ to the total innovation benefit in collaboration relationship $\dot{b}$. The second term in Formula 7 is the importance indicator of innovators, it's described by the standardized ratio of the degree of node *a* to the sum of degree of all nodes in collaboration relationship $\dot{b}$, to a certain extent, this quantifies the importance of node *a* in collaboration relationship $\dot{b}$. $o_m = 2, 3, \ldots, O$ represents the number of game rounds; $x_{a,\dot{b}}(o_m)$ represents the innovation investment made by node *a* to collaboration relationship $\dot{b}$ in the o_m-th round of game; $n_{a,\dot{b}}(o_{m-1})$ represents the innovation benefit attained by node *a* in collaboration relationship $\dot{b}$ after the o_{m-1}-th round of game ends; node *i* represents nodes in collaboration relationship $\dot{b}$, when $i = 0$, it represents node *a* itself; $n_{i,\dot{b}}(o_{m-1})$ represents the innovation benefit attained by node *i* in collaboration relationship $\dot{b}$ after the o_{m-1}-th round of game ends. *x* represents the adjustment coefficient, when *x* is equal to 0, node *a* evenly distributes innovation resources to $l_a + 1$ collaborative relationships in the game; when *x* is greater than 0, node *a* makes more innovation investment to collaborative relationship with a greater node degree and higher early-stage innovation benefit. q_1 $(0 \leq q_1 \leq 1)$ and $1 - q_1$ respectively represent the weight of node degree and the weight of innovation benefit; a greater q_1 value indicates that innovation investment made by innovator tends to collaboration relationship with an advantage in node degree, and a smaller q_1 value indicates that innovation investment made by innovator tends to collaboration relationship with an advantage in innovation benefit; *D* represents the total innovation investment of node *a* in all collaboration relationships.

In CIN, a student innovator will make innovation investment only when he/she chooses to perform collaborative innovation, innovators who choose not to perform collaborative innovation may choose free-riding instead of making innovation investment. However, innovators in the network tend to make collaborative innovation requests to other innovators who have made high innovation investment, so the innovation investment $y_{ai,\dot{b}}(o_m)$ made by node a to other nodes in collaboration relationship $\dot{b}$ after the o_{m-1}-th round of game can be written as:

$$y_{ai,\dot{b}} = \frac{p^{x_{i,\dot{b}}(o_m)}}{\sum_{i=0}^{l_a} p^{x_{i,\dot{b}}(o_m)}} y_{a,\dot{b}}(o_m) \tag{9}$$

According to Formula 9, the investment of collaborative innovation is described by the standardized ratio of the innovation investment of node i in collaboration relationship $\dot{b}$ to the total innovation investment in collaboration relationship $\dot{b}$; assuming: Y represents the collaborative innovation investment made by node a in collaboration relationship $\dot{b}$, $R^* = \{0, 1\}$ represents the strategy set of node a, then the collaborative innovation investment $y_{a,\dot{b}}(o_m)$ made by node a in collaboration relationship $\dot{b}$ can be calculated by the following formula:

$$y_{a,\dot{b}}(o_m) = Y \cdot R_a \tag{10}$$

3.2 Innovation benefit

The conventional game output model that multiplies the input of all nodes by a same output coefficient is not suitable for cases of the collaborative innovation of college students. In order to describe the features of college students' collaborative innovation more accurately, this paper optimized the conventional game output model. In CIN, in view of the differences in the resource endowment and professional advantages of different innovators, in fact, sub-networks in CIN can be regarded as innovation program teams participated by multiple innovators.

In CIN, The output level of innovation benefit of each innovator is determined by its innovation investment and the support given by other innovators in collaboration. Assuming: $\sum_{i=1}^{la} y_{ia,\dot{b}(o_m)}$ represents the collaborative innovation given by all nodes in collaboration relationship $\dot{b}$ in the o_m-th round of game to node a; ω and $1-\omega$ respectively represent the coefficients of the influence of the innovation investment of node a in collaboration relationship $\dot{b}$ and the innovation investment made by node i to node a on its innovation benefit, and it satisfies $0 < \omega < 1$. When $\omega \rightarrow 0$, it means that the technology requirement of node a is high, namely node a has a high requirement for collaborative innovation with other innovators in collaboration relationship. The potential influence of the collaborative innovation between nodes in a same collaboration relationship on the innovation benefit output is represented by α, and it satisfies $0 < \alpha < 1$. The greater the α value, the more obvious the potential influence. The input gain coefficient of the network is represented by s, the greater the value of s, the stronger the input gain ability of the innovation investment. Assuming: ρ_a represents the environmental variable describing the influence of external environment on the innovation benefit output of node a in collaboration relationship $\dot{b}$, and it satisfies $\rho_a \sim M(0, \xi^2)$, then the innovation benefit output $\Omega_{a,\dot{b}}(o_m)$ of node a in collaboration relationship $\dot{b}$ after the o_m-th round of game can be calculated by the following formula:

$$\Omega_{a,\dot{b}}(o_m) = s \cdot \left[\omega x_{a,\dot{b}}(o_m) + (1-\omega) \sum_{i=1}^{l_a} y_{ia,\dot{b}}(o_m) + \alpha x_{a,\dot{b}}(o_m) + (1-\omega) \sum_{i=1}^{l_a} y_{ia,\dot{b}}(o_m) \right] + \rho_a \tag{11}$$

The sum of the innovation benefit output of all nodes in collaboration relationship $\dot{b}$ is the total innovation benefit of collaboration relationship $\dot{b}$ after the o_m-th round of game, it can be calculated by the following formula:

$$\Psi_{\dot{b}}(o_m) = \sum_{i=1}^{l_a} \Psi_{i,\dot{b}}(o_m) \tag{12}$$

In this paper, the innovation benefit of game innovators during the process of collaborative innovation was distributed based on node degree and innovation investment. The distribution method adopted in this paper ignored the evaluation errors of innovators' innovation investment. Assuming: γ represents an adjustment coefficient that has the same meaning and effect as β; q_2, q_3, and q_4 respectively represent the weight of the degree of node a, the weight of investment of collaborative innovation, and the weight of innovation investment, and they satisfy $0 \leq q_2, q_3, q_4 \leq 1$, and $q_2 + q_3 + q_4 = 1$. The net innovation benefit obtained by node a in collaboration relationship $\dot{b}$ after the o_m-th round of game can be calculated by the following formula:

$$n_{a,\dot{b}}(o_m) = \left[q_4 \frac{p^{\gamma \cdot x_{a,\dot{b}}(o_m)}}{\sum_{i=0}^{l_a} p^{\gamma \cdot x_{i,\dot{b}}(o_m)}} + q_3 \frac{p^{\gamma \cdot y_{a,\dot{b}}(o_m)}}{\sum_{i=0}^{k_x} e^{\beta \cdot b_{i,\dot{b}}(t_n)}} + q_2 \frac{p^{\gamma \cdot l_a}}{\sum_{i=0}^{l_a} p^{\gamma \cdot l_i}} \right] \Psi_{\dot{b}}(o_m) - x_{a,\dot{b}}(o_m) - y_{a,\dot{b}}(o_m) \tag{13}$$

According to above formula, the innovation benefit distribution of node a in collaboration relationship $\dot{b}$ is jointly determined by its input indicator and node degree indicator of collaborative innovation in this collaboration relationship.

The total innovation benefit of node a in $l_a + 1$ collaboration relationships after the o_m-th round of game can be calculated by the following formula:

$$N_a(o_m) = \sum_{\dot{b}=0}^{l_a} n_{a,\dot{b}}(o_m) \tag{14}$$

3.3 Update rules of collaborative innovation strategies

At the end of each round of game, node a compares its total innovation benefit $N_a(o_m)$ with the innovation benefit $N_b(o_m)$ of random neighbor node b. If $N_a(o_m) < N_b(o_m)$, node a selects to follow node b to form a collaboration relationship with a probability of Q.

Assuming: L represents the noise intensity indicator of interference caused by external environment and other factors to innovators' collaborative innovation strategy learning process. When L approaches 0, it means that the collaborative innovation strategy of an innovator is not affected by external disturbance, the innovator's collaborative innovation strategy is rational; when L approaches ∞, it means that the collaborative innovation strategy of an innovator is greatly affected by external environment, the innovator cannot make rational decisions of collaborative innovation. In this paper, the simulation probability of collaboration relationship formation of innovators was determined based on the Fermi's golden rule:

$$Q(R_a \to R_b) = \frac{1}{1+e^{\frac{N_a(o_m)-N_b(o_m)}{L}}} \tag{15}$$

4 Experimental results and analysis

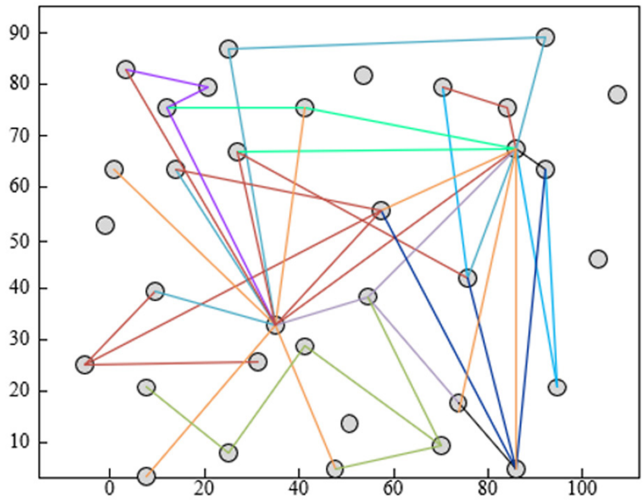

Fig. 3. Dynamic evolution of CIN

Figure 3 shows the dynamic evolution of CIN when node number reaches 50, it gives the structure and state of network evolution simulation. The figure corresponds to the state of CIN in the initial stage of formation, in this stage, with the increase of new nodes preparing to participate in collaborative innovation, the formation of collaboration relationship enhances gradually, and the knowledge exchange between nodes increases as well. The collaboration relationship between nodes is not that tight, the trust degree between innovators is not high, and the depth and breadth of knowledge exchange between network nodes are both insufficient. Only a few nodes maintain a high frequency of interaction with other nodes, most nodes have zero knowledge exchange with others. Figure 4 gives a histogram of the degree of each node, as can be seen from the figure, in this stage, core innovators with a node degree value reaching around 16 appear in the network, the breadth of knowledge flow of such nodes is large but the node number is very small. They form collaborative innovation relationships with many innovators and occupy a core position in the network. Moreover, in this stage, most nodes in the network have a low breadth of knowledge flow and a low node degree value, they haven't formed many collaborative innovation relationships with other nodes yet, and they only have collaborative innovation relationships with a few core innovators.

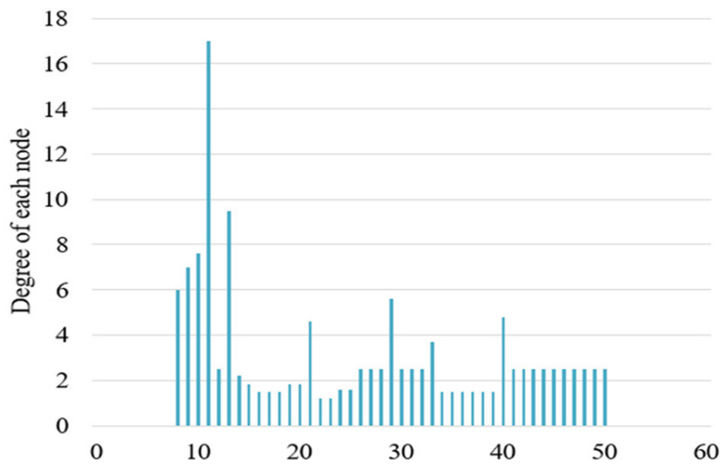

Fig. 4. Distribution of knowledge flow breadth of nodes

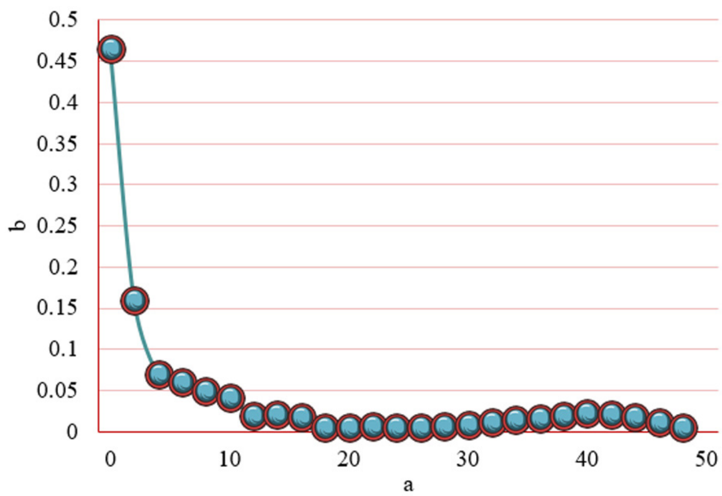

Fig. 5. Distribution of node degree probability

Figure 5 shows the distribution of node degree of CIN when node number reaches 100. The curve is the fitting results of the power distribution of node degree attained in Matlab, the horizontal and vertical coordinates are respectively the network node degree and the probability. The power distribution index and the determinable coefficient *R-square* obtained from the fitting results are 1.416 and 0.7443 respectively, indicating a good fitting effect of node degree, that is, the proposed model basically conforms to the power distribution and the network is scale-free.

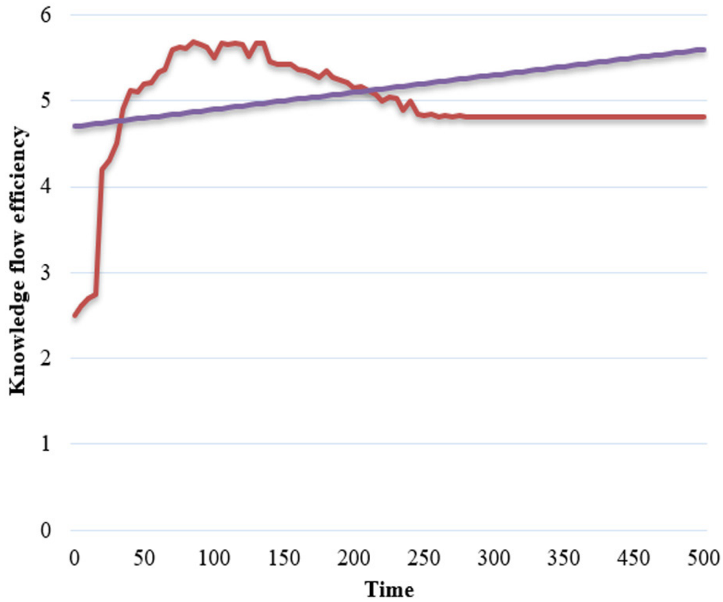

Fig. 6. Variation of knowledge flow efficiency as the network evolves

Figure 6 shows the dynamic changes of knowledge flow efficiency as the network evolves. In this paper, the entire dynamic evolution period was divided into several stages: initial stage I, growth stage II, mature stage III, and renewal stage IV. Growth stage II comes right after initial stage I, during this stage, knowledge flow in the network exhibits a diffusion state, some innovators constantly form collaborative innovation relationships during the development process, and they absorb the knowledge shared by other innovators and the innovation support provided by others, in this stage, the node degree increases, the breadth of knowledge flow grows, and the innovation value is high. In mature stage III, the network pattern is basically formed, the collaborative innovation relationships between innovators gradually strengthen as the trust and knowledge exchange frequency between them grow, in this stage, the node degree and breadth of knowledge flow reach a high level, both the innovation value and innovation benefit are relatively high. In renewal stage IV, some innovators quit and some innovators join, the network structure renews, the knowledge flow efficiency of the network always tends to be stable. On the whole, with the evolution of CIN, the knowledge flow efficiency shows a U-shaped evolution trend.

Table 1 shows the collaborative innovation relationship of some nodes in the network in different stages. As can be seen from the table, as the network evolves, the number of collaborative innovation relationships increases. The number of collaborative innovation relationships in the growth stage II and the mature stage III increases significantly, and this is consistent with previous theoretical analysis.

Table 2 lists the structure evolution indicators of CIN, according to the table data, the development level and node degree of CIN increase gradually, and the increase in growth stage II and mature stage III is obvious, indicating that in these two stages, there are significant improvements in the innovators' ability to control the innovation resources and support provided by other innovators and their own innovation ability. In renewal stage IV, node degree rises slightly, which is consistent with previous theoretical analysis.

Table 1. Collaborative innovation relationship of some network nodes in different stages

Node No.	Initial Stage I		Growth Stage II	
	Relationship Number	Proportion	Relationship Number	Proportion
1	0	0.000	3	0.023
2	70	0.976	127	0.934
3	2	0.015	3	0.016
4	0	0.000	0	0.000
5	0	0.000	2	0.008
6	0	0.000	0	0.000
7	2	0.015	2	0.008
8	12	0.156	40	0.289
9	2	0.017	0	0.000
Node No.	**Mature Stage III**		**Renewal Stage IV**	
	Relationship Number	**Proportion**	**Relationship Number**	**Proportion**
1	28	0.093	52	0.182
2	257	0.972	282	0.994
3	13	0.046	17	0.058
4	3	0.012	4	0.012
5	12	0.043	23	0.077
6	7	0.021	12	0.041
7	16	0.057	25	0.082
8	117	0.436	122	0.427
9	9	0.035	9	0.029

Table 2. Structure evolution indicators of CIN

Period	Initial Stage I	Growth Stage II	Mature Stage III	Renewal Stage IV
Node number	56	110	210	337
Average centrality	13	2.442	6.223	6.445
Average clustering coefficient	0	0.723	0.865	0.874
Average path length	1.26	1.695	1.222	1.195

Figure 7 shows the changes of the distribution ratio of knowledge flow breadth in case of high code number as the network evolves. As can be seen in the figure, as the network scale changes, knowledge flow efficiency and the tightness of collaborative innovation relationships of the network change synchronously. The knowledge flow breadth of nodes shows an opposite trend of variation as the network scale changes, it can be inferred from the relationship among the three that in order to make sure the CIN has reasonable knowledge flow breadth of nodes, knowledge flow efficiency, and tightness of collaborative innovation relationships, the scale of CIN should neither be too large or too small. A moderate scale of CIN can ensure that the formation of collaboration relationships won't be too hard, and it can also guarantee the efficiency of knowledge flow; moreover, the ways for innovators to gain innovation knowledge won't be too few, and the innovation value output will be maintained at a high level.

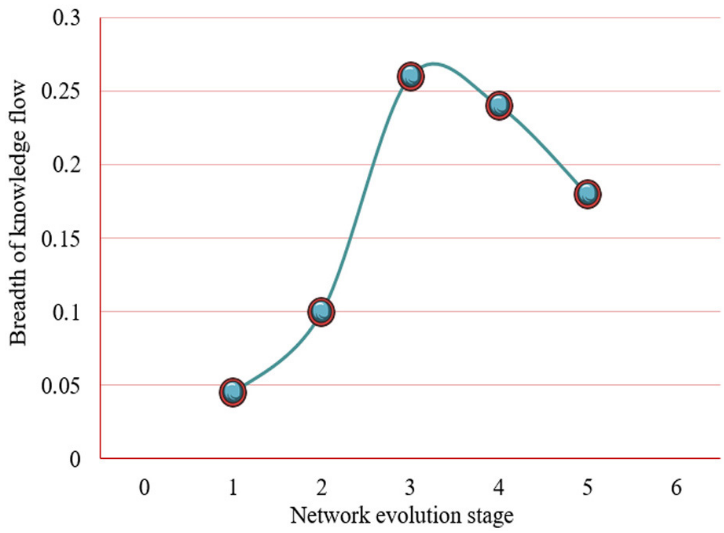

Fig. 7. Distribution ratio of knowledge flow breadth in case of high node number as network evolves

5 Conclusion

This paper studied the structural evolution features of CIN of college students from the perspective of knowledge flow. In the second chapter, this paper showed the network-shaped knowledge flow pattern, built a model to reflect the innovators' citation of innovation knowledge and the interaction between related factors and their interaction space, and analyzed the distance attenuation of knowledge flow of CIN and its evolution trend. In the third chapter, this paper combined the structure of CIN with EG, built an EG model for CIN, and analyzed the evolution law of college students' collaborative innovation behavior in CIN. In the experiment, the dynamic evolution of CIN in case of a node number of 50 was analyzed, a histogram of the nodes was plotted, and the distribution of the probability of node degree of CIN in case of a node number of 100 was given. The paper divided the entire network evolution period into several stages: initial stage I, growth stage II, mature stage III, and renewal stage IV, and drew a conclusion that with the evolution of CIN, the knowledge flow efficiency shows a U-shaped evolution trend. Moreover, the collaborative innovation relationships of some nodes in the network in different stages and the structure evolution indicators of CIN were given, and the analysis results are consistent with previous theoretical analysis. At last, this paper also showed the changes of the distribution ratio of knowledge flow breadth in case of high code number as the network evolves, and it's known that as the network scale changes, knowledge flow efficiency and the tightness of collaborative innovation relationships in the network change synchronously, and the knowledge flow breadth of nodes shows an opposite trend of variation as the network scale changes.

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