The Multi-Factor Action Mechanism of Knowledge Flow on Collaborative Innovative Learning Platforms for College Students

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Abstract—Knowledge flow is an explicit behavior of college students during their Collaborative Innovative Learning (CIL). Existing studies on the management mechanism of knowledge flow on CIL platforms generally lack a systematic theoretical analysis on the action mechanism of the influencing factors, few scholars have viewed the problems of the management mechanism of knowledge flow, the action mechanisms of the influencing factors of knowledge flow, the efficiency of knowledge flow, and the relationship among them from the perspective of the platform, and few studies have discussed the impact of the management mechanism of CIL platforms on the knowledge flow from a dynamic angle. To fill in these research blanks, this paper aims to analyze the multi-factor action mechanism of knowledge flow on CIL platforms for college students. At first, this paper elaborated on the formation mechanism of the CIL network, and measured model variables of the proposed network; then, it analyzed the robustness of the functions of the proposed network based on knowledge flow; at last, this paper gave the multi-factor variable analysis results of the model.

Keywords—collaborative innovative learning (CIL), knowledge flow, multi-factor variable, robustness, action mechanism, learning platform

1 Introduction

In response to policy guidance, colleges and universities have established various CIL platforms to help students improve their innovation ability and realize the agglomeration and accumulation of innovation resources [1–7]. The knowledge stored on CIL platforms is an important component of CIL resources for college students, and the knowledge flow is a kind of explicit behavior of college students during their CIL process [8–16]. However, existing CIL platforms for college students generally have unsolved issues such as the cooperation of CIL only stays at a low level, the inefficient knowledge flow, and the unsmooth communication between innovation participants [17–21]. To ensure orderly operation and fluent knowledge flow of CIL platforms, it's a necessary work to effectively gather and allocate innovation resources to promote the sustainable development of CIL platforms and help college students enhance their innovation ability.

Alexander [22] formed a cohesive and highly functional team consisted of students majoring in business, management, marketing, electrical, civil, mechanical and electromechanical engineering, and other disciplines, and helped them work and innovate effectively, they introduced the seminars hold by the student team, the reflections and feedback given by students, and the experiences gained based on teacher observation and student performance. Wright [23] argued that students should possess an understanding of innovation and related skills (such as creativity, the ability to discover and conclude problems, and the ability to create new ideas and develop them into practical and useful products, etc.) so as to keep up with or take a lead in the fast development of science and technology in the 21 century, and they proposed the method of letting students participate in innovation workshops to help them develop innovation ability. Koch et al. [24] proposed that now creative and effective innovation has become increasingly important in engineering design, they experimented on design teams consisted of more than 25 students during engineering design class to measure the relevance and utility of collaboration and knowledge sharing between and within design teams. Through research, the authors discovered a few specific issues and opportunities to help students majoring engineering design to get in line with the increasingly networked and distributed professional engineering environment upon graduation. Wang et al. [25] believe that knowledge flow is the core activity of innovation networks. Major issues faced by companies in this knowledge economy era include how to promote knowledge flow in innovation networks and how to increase their sustainable advantages in competitions, for these unsolved issues, they summarized four informal governance mechanisms based on existing studies, namely trust, reputation, cooperation culture and joint sanctions; then the authors took the questionnaire data of 227 companies as samples, and adopted a method called fsQCA to study the relationship between knowledge flow, informal governance mechanisms, and network power. Zhang and Ding [26] hold that collaboration network and knowledge network are important channels of information transmission and knowledge flow and they can assist network participants in information update and knowledge creation; however, only a few existing studies have compared the knowledge flow in the two networks, so the authors analyzed the evolution of the two networks from the perspectives of network type, node centrality, and core-periphery structure, and the results indicate that the two networks are decoupling and developing in negative directions.

Existing studies on the management mechanism of knowledge flow on CIL platforms generally lack a systematic theoretical analysis on the action mechanism of the influencing factors. Few scholars have viewed the problems of the management mechanism of knowledge flow, the action mechanisms of the influencing factors of knowledge flow, the efficiency of knowledge flow, and the relationship among them from the perspective of the platform. At the same time, the dynamic and complex processes of feedback between various influencing factors of knowledge flow haven't been fully considered, that is, few studies have discussed the impact of the management mechanism of CIL platforms on the knowledge flow from a dynamic angle. Thus, to make up for these shortcomings, this paper aims to analyze the multi-factor action mechanism of knowledge flow on CIL platforms for college students. In the second chapter, this paper elaborated on the formation mechanism of the CIL network; in the third chapter, the model variables of the proposed network were measured; in the fourth chapter, this paper analyzed the robustness of the functions of the proposed network based on knowledge flow; in the last part, this paper gave the multi-factor variable analysis results of the model.

2 Formation mechanism of the CIL network

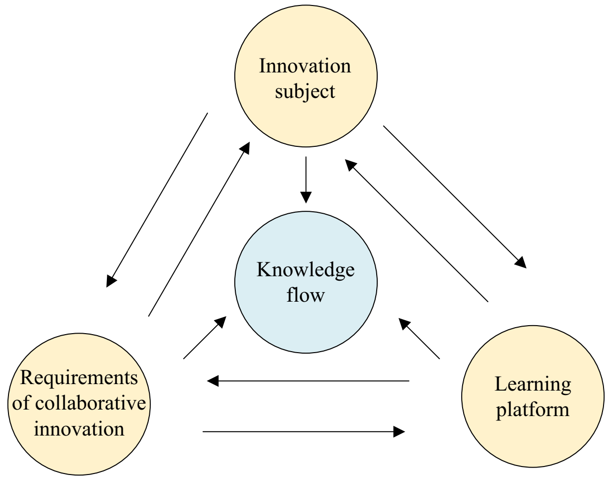

Fig. 1. Action path of knowledge flow in the CIL network

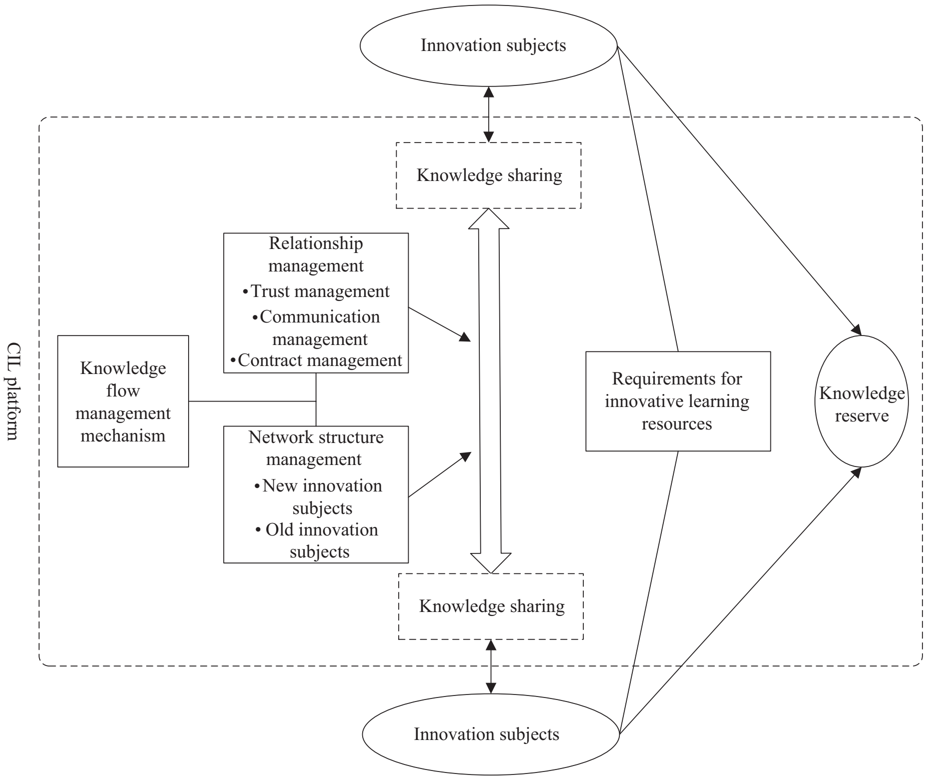

Fig. 2. Model of the impact of management mechanism of CIL platform on knowledge flow

On CIL platforms, college students are usually the subjects in innovation, so this paper took them as network nodes to construct the CIL network. Figure 1 shows the action path of knowledge flow in the CIL network. According to the figure, the innovation subjects are the suppliers and demanders of knowledge flow in the CIL network, and there're interactive relationships among the properties of innovation subjects, the requirements of collaborative innovation, and the knowledge structures of the learning platforms, and they work together to affect the knowledge flow. Connection edges in the network represent the correlations among network nodes, and the network was built based on the purpose of knowledge exchange. In this paper, the functions of the connection edges in the network were realized via controlling the node status of the CIL network in knowledge flow evolution stage.

Innovation subjects in the CIL network include enterprises, colleges and universities, and research institutions, etc., they are the senders and receivers of knowledge flow in the CIL network, and the relationships among them would affect the acquisition method and degree of knowledge flow in the network, and the structure of the network is the channels of knowledge flow. There're interactive relationships among node attribute, network relationship, and structure degree, they jointly affect knowledge flow in the CIL network, and ultimately form the micro action path of knowledge flow in the CIL network.

Figure 2 gives a model reflecting the impact of the management mechanism of CIL platform on knowledge flow. Knowledge flow on the platform is realized by the knowledge sharing of college students, and their knowledge difference is effectively reduced through the demand and supply of knowledge, and finally the knowledge advantages of the platform will be improved. In order to effectively promote knowledge flow on the platform, it's necessary to formulate relationship management and network structure management mechanisms, promote communication and collaboration among innovation subjects, and build a good cooperative relationship of CIL.

In the formation stage of the CIL network, as college students begin to enter the platform to conduct CIL activities, cooperative relationship gradually form among innovation subjects but is not stable yet. Then, in the growth stage of the CIL network, more college students enter the platform for CIL, and such cooperative relationship becomes closer and steadier. After that, as the speed of college students entering the platform slows down, the scale of the network stabilizes, as some new innovation subjects join in the platform, some old innovation subjects will quit as well.

For a given moment p = 0, assuming n_e represents the initial number of nodes (innovation subjects) in the CIL network, every time a new innovative subject joins in the network, it will form s connection edges with the original nodes in the network; the probability of connection edge formation $\delta(l_i)$ and the node degree of new innovation subject l_i would exhibit same change trend, then there is:

$$\delta(l_i) = \frac{l_i}{\sum_j l_i} \tag{1}$$

With the expansion and evolution of the CIL network, the number of nodes in the network increases to $M = p + n_e$, and the number of connection edges becomes s.

Nodes (namely innovation subjects) with more connection edges and high connectivity have greater impact on the efficiency of knowledge flow between nodes in the CIL network.

3 Multi-factor variable measurement of the network model

The node degree of the CIL network is the total number of edges connecting nodes (innovation subjects) in the network. Assuming: $t(l)$ represents the distribution function for measuring the probability that the node degree value of a node is equal to l; M represents the total number of nodes in the CIL network; then the value of $t(l)$ could be calculated by comparing the number of nodes with a node degree value of l_i with M, that is:

$$t(l) = \frac{\sum_{i=1}^{M} r(l - l_i)}{M} \tag{2}$$

The node degree of the CIL network conforms to the power-law distribution of $t(l) = \beta l^{-\alpha}$, by taking the double logarithm of $t(l)$, we can get: $logp(l) = logak^{-\alpha}$ $logp(l) = loga\beta - \alpha logl$.

In this paper, the in-degree of nodes in the CIL network is defined as that an innovation subject obtains innovative learning resources from other nodes, it is a knowledge demander; the out-degree of nodes is defined as that an innovation subject's innovative learning resources are obtained by other nodes, it is a knowledge supplier; then, the in-degree $l_i(in)$ and out-degree $l_i(out)$ of nodes (innovation subjects) participating in the knowledge flow of the CIL network can be calculated by the following formulas:

$$l_i = \sum_{j=1}^{M} x_{ij} \tag{3}$$

$$l_i(in) = \sum_{j=1}^{M} x_{ji} \tag{4}$$

$$l_i(out) = \sum_{j=1}^{M} x_{ij} \tag{5}$$

The arithmetic mean of node degree is defined as the mean degree <l> of the CIL network, which can be calculated by the following formula:

$$\langle l \rangle = \frac{1}{M} \sum_{j=1}^{M} l_i = \frac{1}{M} \sum_{i=1}^{M} \sum_{j=1}^{M} x_{ij} \tag{6}$$

<l> represents the closeness degree of the cooperative relationship among innovation subjects in the CIL network. The greater the value of <l>, the closer the cooperative relationship; the smaller the value of <l>, the looser the cooperative relationship.

In the CIL network, if a node u_i establishes cooperative relationship with other l_i nodes, and these l_i nodes may have cooperative relationship with other $l_i(l_i - 1)/2$ nodes, then the calculation formula of clustering coefficient D_i (the ratio of actual number of connection edges between node u_i and its l_i CIL collaborators to the maximum number of possible connection edges) is:

$$D_i = \frac{O_i}{l_i(l_i-1)/2} = \frac{2O_i}{l_i(l_i-1)} \tag{7}$$

When the distance between nodes in the CIL network is quantified based on the citation relationship of innovative learning resources, since it's hard to describe it using geographic distance, this paper defines the minimum number of possible connection edges between nodes u_i and u_j as the distance e_{ij} between the two, then the average path length of the CIL network can be calculated by the following formula:

$$APL = \frac{1}{M^2}\sum_{i=1}^{M}\sum_{j=1}^{M} e_{ij} \tag{8}$$

In this paper, the maximum reachable distance of knowledge of the CIL network is defined as the network diameter E, which can be calculated by the following formula:

$$E = \max_{1 \le i, j \le M} e_{ij} \tag{9}$$

The average shortest path of all connections to the node in the CIL network can be calculated by the following formula:

$$k = \frac{1}{\frac{1}{2}M(M+1)}\sum\nolimits_{i>j} e_{ij} \tag{10}$$

This paper used the structural hole to measure the structural embeddedness of the CIL network. Assuming: i represents the target node in each time window; j represents another node connected to node i; w represents a third node in the network other than i and j; T_{iw} represents the proportional intensity of the connection between i and w; n_{jw} represents the marginal intensity of the connection between j and w; E_i represents the actual network size of node i, then the following formula gives the calculation method of the structural hole efficiency index:

$$\eta_i = \left[\sum_j \left(1 - \sum_w t_{iw} n_{iw}\right)\right] / E_i \tag{11}$$

This paper uses the average structural hole level of network nodes (namely the innovation subjects on a CIL platform) to describe the embeddedness level of the knowledge network structure. Assuming: M represents the number of nodes owned by the CIL platform within each time window, i represents nodes in the corresponding time window, then there is:

$$\eta_i^* = \frac{1}{M}\sum_{i=1}^{M}\left\{\left[\sum_j \left(1 - \sum_w t_{iw} n_{jw}\right)\right] / E_i\right\} \tag{12}$$

Assuming: i represents target node in each time window, if there is a connection between nodes i and j in the CIL network, then A_{ij} is 1, otherwise it is 0; assuming $(M-1)$ represents the maximum number of possible connection edges of node i in the network, then the quantification of relational embeddedness level of the CIL network is given by the following formula:

$$REL(m_i) = \sum_i A_{ij} / (M-1) \tag{13}$$

This paper uses the average relational embeddedness level of network nodes owned by the CIL platform to measure the relational embeddedness level of knowledge flow of the CIL platform. Assuming: M' represents the number of nodes owned by the CIL platform in each time window, then there is:

$$REL^*(m_i) = \frac{1}{M'} \sum_{i=1}^{M'} \left[\sum_i A_{ij} / (M-1) \right] \tag{14}$$

When the m-th type of knowledge of a node (innovation subject) flows into innovation subject nodes, the change in the knowledge reserve of nodes in the network can be represented by the following formulas:

$$KT_{ip} = KS_{ip} + \frac{m_{ip} * KNA_{ip}}{2} \tag{15}$$

$$KT_p = \sum KT_{ip} \tag{16}$$

When a new innovation subject is introduced into the network within per unit time, if m' connection edges are created between innovation subjects in the previous time period, then the volume of knowledge flow between nodes can be calculated by the following formulas:

$$KE_{ip+1} = KE_{ip} + m'_{ip} \tag{17}$$

$$KF_{ip} = \frac{m'_{ip}}{2} \tag{18}$$

$$KF_p = \sum KF_{ip} \tag{19}$$

4 Robustness of the network model

Since the development of CIL platform depends on the flow and exchange of various knowledge during college students' CIL activities, the robustness analysis of the functions of the CIL network formed by such knowledge flow should start from the network structure. In view of the robustness features of the CIL network, this paper pays more attention to the retained network performance after innovation subjects quit the platform or the cooperation between innovation subjects is ended, that is, it aims to measure the reachable range of knowledge of the network structure and the knowledge flow efficiency which reflects the robustness of network functions, the two are described respectively by the maximum connected subgraph and the network efficiency to achieve the measurement of the robustness of the CIL network. Assuming: M represents the number of innovation subject nodes in current network; m^* represents the number of maximum connected subgraph nodes in the network; w represents the number of nodes that tend to quit due to other interferences; $R(w)$ represents the proportion of the size of maximum connected component in the node, then the robustness index could be expressed as:

$$R(w) = \frac{m^*}{M} \tag{20}$$

The knowledge flow efficiency of the CIL network is related to APL, the smaller the value of APL, the higher the knowledge flow efficiency of the network. When old innovation subjects quit the network, the number of cooperative relationships among innovation subjects would change accordingly, the average shortest path connecting the innovation subject nodes would be affected, and the knowledge flow efficiency of the network would cause changes in the robustness of the network as well. In this paper, APL was standardized in order to quantitatively describe the robustness of the CIL network under different evolution states, the calculation formula of knowledge flow efficiency η_H is given by Formula 27:

$$\eta_H = 1 - \frac{1}{M(M-1)} \sum_{i \neq j} \frac{1}{e_{ij}} \tag{21}$$

$\eta_H = 0$ indicates that the knowledge flow efficiency of the CIL network is the lowest, which means that the innovation subjects in the network are all in a knowledge-independent state, there's no knowledge exchange between them. The closer the value of η_H is to 1, the higher the knowledge flow efficiency of the CIL network, which means that the knowledge flow between innovation subjects in the network is smoother.

5 Experimental results and analysis

Table 1 lists the measurement results of variables of the network model. Based on the existing research results and the differences in the requirement orientations and competition properties of the CIL of different innovation subjects, this paper classified students from a same college into one category, and the values of the corresponding nodes (innovation subjects) were assigned to 1; while those from other institutions or the common persons in society were classified as another category, and the values of the corresponding nodes were assigned to 0. If the measurement result of a variable is less than the median, then it means that the performance of the network is not satisfactory in terms of this index; if the measurement result is greater than the median, then it means that the performance of the network in terms of this index is satisfactory.

Table 1. Measurement results of variables in the network model

Variable Name	*KT*	*KE*	*REL*	*APL*	*t*(*l*)	*D*	Structural Hole
Maximum	584.021	152.148	23.158	3.521	0.052	0.69	0.028
Minimum	4.174	0.025	4.625	0.011	0.036	0.51	0.084
Mean	85.427	23.158	8.411	0.695	0.014	0.19	0.073
Standard deviation	184.572	35.241	5.295	0.713	0.025	0.095	0.061
Median	17.524	8.352	6.112	1.625	0.0219	0.57	0.036

Table 2. Measurement results of the collaborative innovation level of on-campus and off-campus networks

Scope	Off-Campus				On-Campus			
Network Structure	Centrality > Structural Hole		Centrality < Structural Hole		Centrality > Structural Hole		Centrality < Structural Hole	
Relationship	Deep	Not Deep	Deep	Not Deep	Deep	Not Deep	Deep	Not Deep
Number of samples	19	5	11	47	69	2	7	3
Total knowledge volume	116.295	184.35	182.57	115.429	46.295	98.358	174.529	136.258
Collaborative innovation level	0.315	0.195	−0.418	0.795	0.059	0.048	0.085	−0.062

Table 3. Measurement results of the collaborative innovation level of overall network

Scope	Overall			
Network Structure	Centrality > Structural Hole		Centrality < Structural Hole	
Relationship	Deep	Not Deep	Deep	Not Deep
Number of samples	85	13	27	55
Total knowledge volume	65.847	112.625	169.358	142.581
Collaborative innovation level	0.582	0.062	−0.147	−0.485

To minimize the differences in the measurement standards of different model variables, this paper standardized the cooperative relationship type and collaborative innovation level of the CIL network, and Tables 2 and 3 respectively give the measurement results of the collaborative innovation level of on-campus, off-campus, and overall networks. With the help of SPSS and R language software, this paper conducted two-factor variance analysis on the knowledge flow status and collaborative innovation level of college students from two perspectives: the relationship between centrality and structural hole, and the depth of cooperative relationship, and judged whether there're significant differences in the analysis results from different perspectives, further, the matching of college students' CIL relationships was analyzed as well.

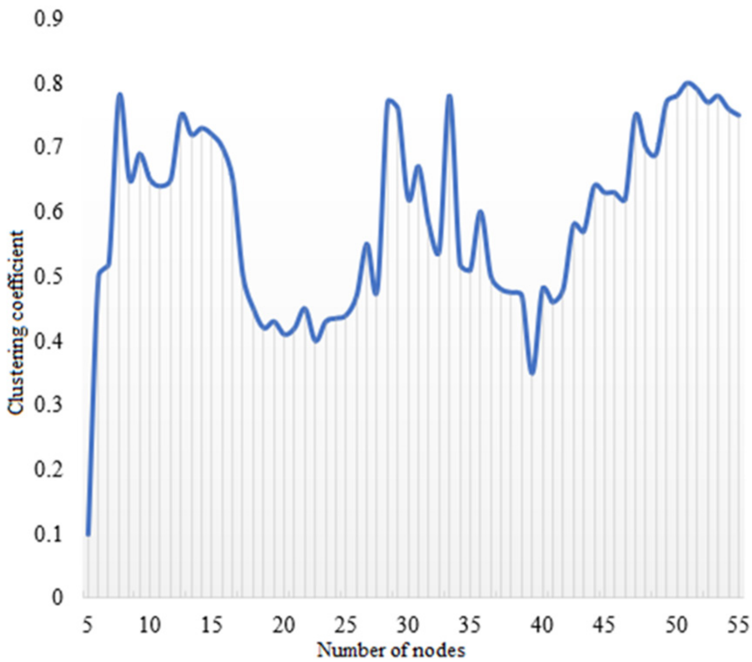

Fig. 3. The change of clustering coefficient during network evolution

Figure 3 shows the change of the clustering coefficient during the process of network evolution. With the progress of network evolution, clustering coefficient fluctuates and shows an upward trend on the whole. In the early stage of evolution, the cooperative relationship between innovation subjects has just been established, and the clustering effect is not obvious. Then, as new innovation subjects join in the network constantly, innovation subjects with better knowledge advantages emerge in the network, groups of innovation subjects with different requirements and learning objectives form gradually, and the clustering coefficient increases slowly. When the network reaches a certain scale, some old innovation subjects choose to quit, which leads to a decline in the clustering coefficient.

Figure 4 shows the change of the average path length during the process of network evolution. As can be seen from the figure, the average path length of the CIL network fluctuates around 1.5, the lower the value, the higher the knowledge flow efficiency of the network. In the early stage of evolution, innovation subjects with better knowledge advantages have not yet appeared in the network, college students' requirement for collaborative innovation is not high, and the reachable range of knowledge flow is narrow. Then, as new innovation subjects join in the network constantly, the network scale expands gradually, and nodes (innovation subjects) in the network actively seek to cooperate with other nodes with similar objectives and requirements of collaborative innovation. At this time, the average path length of the network begins to increase until the node has a clearer understanding of the knowledge supply and demand situations of other nodes, and the formation of cooperative relationship in the network becomes easier. When the network expands to a certain scale and old innovation subjects begin to quit, the average path length of the network would decrease.

Figures 5 and 6 show the changes of knowledge flow and total knowledge volume during network evolution. Overall speaking, as the number of nodes increases, knowledge flow and total knowledge volume both show an upward trend. Then, with the progress of network evolution, the intensity of correlation between innovation subjects who have already established stable cooperative relationship increases constantly, the trust between them increases, which ensures smooth knowledge flow in the network, and this will further deepen the collaborative innovation level of innovation subjects. As more innovation subjects join the network, the amount of knowledge resources that could be attained by the nodes increases gradually, and the total knowledge volume grows significantly as well. The increase of connection edges means that the nodes have more CIL opportunities, and the knowledge flow grows obviously, too.

Figure 7 shows the change of network robustness level under different interference forms. According to the robustness analysis of the network model, the robustness level of the CIL network is higher when innovation subjects quit randomly, and the robustness level is lower when they quit determinately. Under the interference form that old innovation subjects quit randomly, the continuous quit of innovation subjects can cause greater damages to the CIL network.

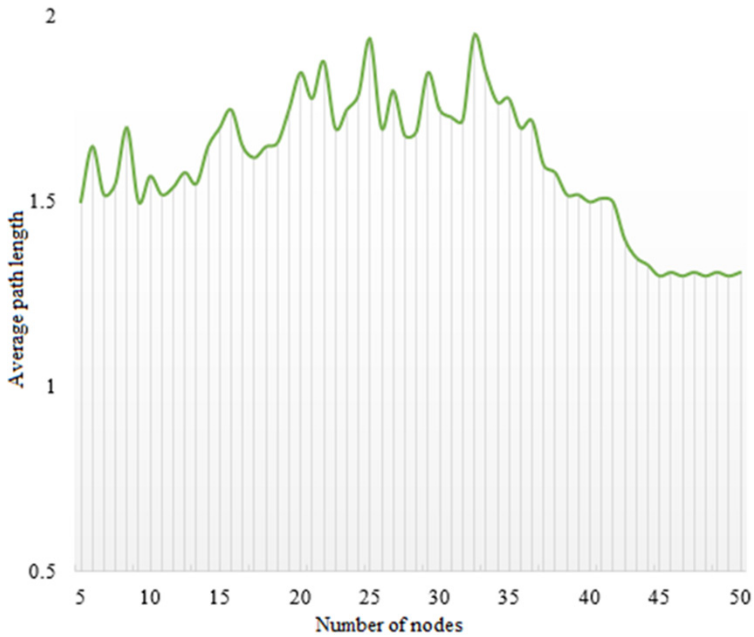

Fig. 4. The change of average path length during network evolution

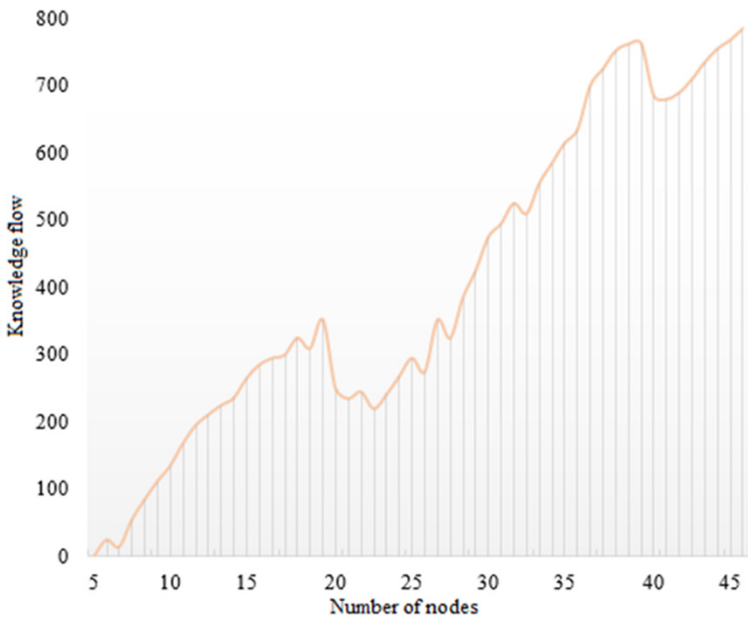

Fig. 5. The change of knowledge flow during network evolution

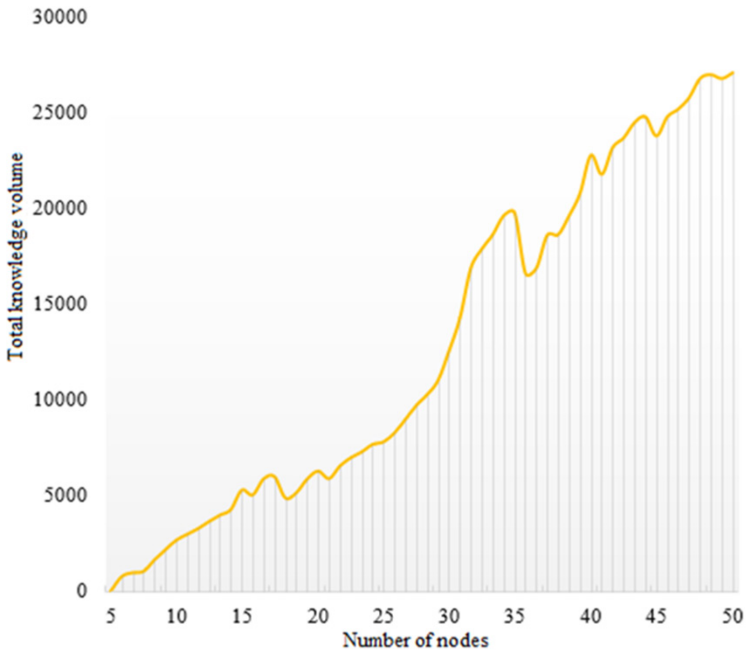

Fig. 6. The change of total knowledge volume during network evolution

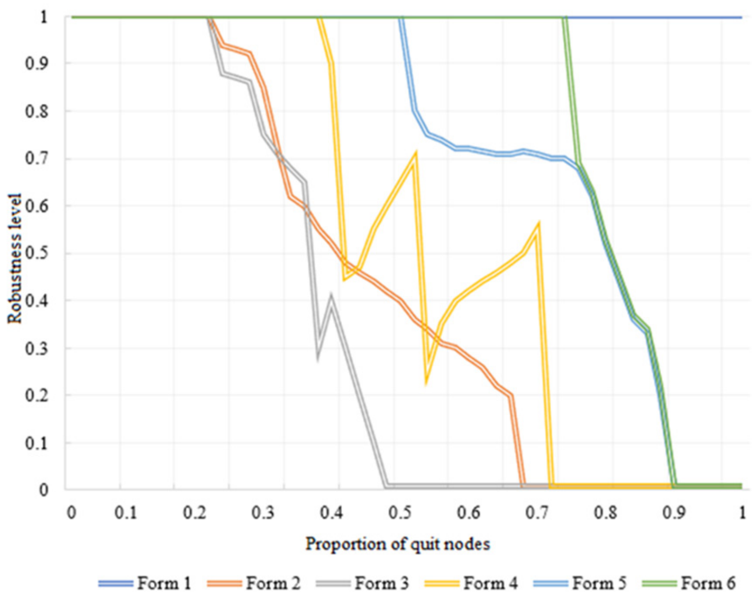

Fig. 7. Network robustness level under different interference forms

6 Conclusion

This paper studied the multi-factor action mechanism of knowledge flow on CIL platforms for college students. At first, the paper introduced the formation mechanism of the CIL network in detail, measured the variables of the network model, and analyzed the robustness of the functions of the CIL network. In the experiment, this paper gave the measurement results of the network model variables and the collaborative innovation level of on-campus, off-campus, and overall networks, and analyzed the changes of clustering coefficient, average path length, knowledge flow, and total knowledge volume during the network evolution process. Also, this paper gave the change of the network robustness level under different interference forms, and the results showed that the continuous quit of innovation subjects can cause greater damages to the CIL network.

7 References

[1] Zhang, L. (2021). Construction of university students innovation and entrepreneurship resource database based on collaborative big data analysis. In EAI International Conference, BigIoT-EDU, 185–193. https://doi.org/10.1007/978-3-030-87903-7_25

[2] Mivehchi, L., Rajabion, L. (2020). A framework for evaluating the impact of mobile games, technological innovation and collaborative learning on students' motivation. Human Systems Management, 39(1): 27–36. https://doi.org/10.3233/HSM-190543

[3] Wang, X. (2020). College students' innovation and entrepreneurship resources recommendation based on collaborative filtering and recommendation technology. In Journal of Physics: Conference Series, 1533(2): 022013. https://doi.org/10.1088/1742-6596/1533/2/022013
[4] Adorjan, A., Nunez-Del-Prado, M. (2018). Fostering 21 century learning and innovation competencies through students' online collaborative activities in software engineering courses. In 2018 IEEE World Engineering Education Conference (EDUNINE), 1–4. https://doi.org/10.1109/EDUNINE.2018.8450987
[5] Pearson, M., Singelmann, L., Striker, R., Vazquez, E.A., Swartz, E. (2020). Benefits of long-distance collaboration in higher education institutions to train students in innovation practices. 2020 ASEE Virtual Annual Conference Content Access. https://doi.org/10.18260/1-2--34203
[6] van den Berg, C. (2019). Teaching digital innovation: collaboration between students and entrepreneurs. in European conference on innovation and entrepreneurship. Academic Conferences International Limited. Proceedings of the 14th European Conference on Innovation and Entrepreneurship, ECIE 2019, 2: 1061–1068. https://doi.org/10.34190/ECIE.19.078
[7] Xu, X., Shen, J. (2018). Multi-dimension training scheme to improve the innovation capacity of postgraduate and undergraduate students collaboratively. In 2018 IEEE Frontiers in Education Conference (FIE), 1–4. https://doi.org/10.1109/FIE.2018.8658508
[8] Sasidharan, S. (2019). Reconceptualizing knowledge networks for enterprise systems implementation: incorporating domain expertise of knowledge sources and knowledge flow intensity. Information & Management, 56(3): 364–376. https://doi.org/10.1016/j.im.2018.07.010
[9] Yeo, D., Bae, J.H. (2019). Multiple flow–based knowledge transfer via adversarial networks. Electronics Letters, 55(18): 989–992. https://doi.org/10.1049/el.2019.1874
[10] Peng, G. (2019). Co-membership, networks ties, and knowledge flow: An empirical investigation controlling for alternative mechanisms. Decision Support Systems, 118: 83–90. https://doi.org/10.1016/j.dss.2019.01.005
[11] Chang, C.L., Lin, C.Y., Lai, K.K., Chen, H.C. (2019). The role on inter-organizational knowledge flows of patent citation network: The case of Thin-film solar cells. In 2019 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), 1–8. https://doi.org/10.1109/ICE.2019.8792574
[12] Zhao, J., Xi, X., Yi, S. (2015). Resource allocation under a strategic alliance: How a cooperative network with knowledge flow spurs co-evolution. Knowledge-Based Systems, 89: 497–508. https://doi.org/10.1016/j.knosys.2015.08.016
[13] Suppakitpaisarn, V., Dai, W., Baffier, J.F. (2015). Robust network flow against attackers with knowledge of routing method. In 2015 IEEE 16th International Conference on High Performance Switching and Routing (HPSR), 1–8. https://doi.org/10.1109/HPSR.2015.7483079
[14] Ye, X., Zhang, J., Liu, Y., Su, J. (2015). Study on the measurement of international knowledge flow based on the patent citation network. International Journal of Technology Management, 69(3–4): 229–245. https://doi.org/10.1504/IJTM.2015.072971
[15] Zhao, J.Y., Li, B.Z., Xi, X., Wu, G.D., Wang, T.N. (2018). Research on the characteristics of evolution in knowledge flow networks of strategic alliance under different resource allocation. Expert Systems with Applications, 98: 242–256. https://doi.org/10.1016/j.eswa.2017.11.012
[16] Segarra, L., Herrera, R.F., Alarcón, L.F., Pellicer, E. (2017). Knowledge management and information flow through social networks analysis in Chilean architecture firms. In Proc. of the 25th Ann. Conf. of the Int'l Group for Lean Construction, 413–420. https://doi.org/10.24928/2017/0244

[17] Chang, Y.H., Lai, K.K., Lin, C.Y., Yang, W.G., Shih, P.J., Liu, C.C. (2017). Knowledge converter(s) within knowledge flows of patent citation network: evidence from patent lawsuits of smartphones. In 2017 Portland International Conference on Management of Engineering and Technology (PICMET), 1–8. https://doi.org/10.23919/PICMET.2017.8125422
[18] Kerzazi, N., El Asri, I. (2016). Knowledge flows within open source software projects: A social network perspective. In International Symposium on Ubiquitous Networking, 397: 247–258. https://doi.org/10.1007/978-981-10-1627-1_19
[19] Leon, R.D., Rodríguez-Rodríguez, R., Gómez-Gasquet, P., Mula, J. (2017). Social network analysis: A tool for evaluating and predicting future knowledge flows from an insurance organization. Technological Forecasting and Social Change, 114: 103–118. https://doi.org/10.1016/j.techfore.2016.07.032
[20] Pereira, T., Neto, M., Victorino, G. (2017). Information and knowledge-intensive firm: uncovering information flows at Amorim cork composites using social network analysis. In Proceedings of the 2017 International Conference on Information System and Data Mining, 44–50. https://doi.org/10.1145/3077584.3077602
[21] Zhang, Z., Ma, W., Liu, G., Chen, Y. (2013). Modeling the knowledge flow network for collaborative design process. In DS 75–6: Proceedings of the 19th International Conference on Engineering Design (ICED13), Design for Harmonies, 6: 301–310.
[22] Alexander, D.G. (2016). Cross-disciplinary collaboration and innovation for engineering and business student teams. In 2016 ASEE Annual Conference & Exposition. https://doi.org/10.18260/p.26607
[23] Wright, G. (2009). Increasing student innovation ability and aptitude through collaborative cross-discipline technology enhanced innovation boot camps. In Society for Information Technology & Teacher Education International Conference, 3100–3103.
[24] Koch, M.D., Schulte, R.J., Tumer, I.Y. (2010). The effects of open innovation on collaboration and knowledge sharing in student design teams. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, 44144: 811–819. https://doi.org/10.1115/DETC2010-29008
[25] Wang, T., Li, X., Wang, Z., Zhang, Y. (2020). Informal governance mechanism, network power and knowledge flow of enterprise innovation network. In 2020 International Conference on Advance in Ambient Computing and Intelligence (ICAACI), 81–88. https://doi.org/10.1109/ICAACI50733.2020.00022
[26] Zhang, Y.R., Ding, M.A. (2016). Modeling the evolution of collaboration network and knowledge network and their effects on knowledge flow through social network analysis. Journal of Digital Information Management, 14(4): 246–254.

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