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PAPER

Learning Analytics in Education: A Social Network-Based Approach for Analyzing the Interaction and Influence of Collaborative Learning Communities

Chunling Ren[1](✉), **Zheng Qi**[2]

[1]School of Electrical Engineering, Changzhou Vocational Institute of Mechatronic Technology, Changzhou, China

[2]School of Creative Design, Changzhou Vocational Institute of Mechatronic Technology, Changzhou, China

v.bin@163.com

ABSTRACT

Collaborative learning is viewed as an increasingly important learning mode in higher vocational education these days. In this mode, students are no longer passive receivers of knowledge, but take the roles of creators and sharers, and figuring out the interactive and collaborative relationships between students is particularly important for understanding the pattern and structure of student interaction. With the help of social network analysis methods, this study investigated the social network features of collaborative learning communities, measured the parameters of these network features, analyzed the accessibility of community members, and revealed the influence of members in the community based on the Lead index. The findings of this paper give deeper understandings and new insights into the collaborative learning mode and provide useful evidences for the optimization of collaborative learning strategies.

KEYWORDS

higher education, collaborative learning, social network analysis, connection degree of nodes, lead index

1 INTRODUCTION

As the techniques and concepts of modern education are developing, collaborative learning has become a considerable teaching strategy, especially in the field of higher vocational education [1–3]. In collaborative learning, students are no longer the passive receivers of knowledge, but take the roles of creators and sharers. A substantive distinguishing feature of higher vocational education is the emphasis on team work and practical operation, so it's a meaningful work to study the interaction between students and their collaborative relationship during collaborative learning [4–7].

Social network analysis is an approach for studying interpersonal relationships, thus it can also be used to figure out the pattern and structure of student interaction in learning communities [8, 9]. In a collaborative learning environment, each student is

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a node and their interactions constitute a complex network structure, and analyzing this structure can help educators better understand the behavioral patterns of learners and instruct them to engage in collaborative learning more effectively [10–14].

Although social network analysis has been widely used in several research areas, in the field of education, especially in terms of collaborative learning, it has some obvious defects and shortcomings [15, 16]. Conventional analysis methods tend to over-simplify the interaction mode between learners, and ignore some key parameters in the network [17, 18]. The evaluation of learners' influence is neither intensive nor extensive enough, resulting in education decisions that may be made based on incomplete or biased information.

The objective of this study is to investigate the social network features of collaborative learning community. The content of the paper is divided into three parts: the first part is the measurement and calculation of the feature parameters of collaborative learning community, including the connection degree of member nodes, the network density, and the clustering coefficient; the second part is an analysis of the accessibility of members in the collaborative learning community, which can reveal the interaction pattern between learners; the third part is an analysis of the influence of members in the learning community based on the *Lead* index and the centrality of the member node accessibility. These findings can offer a more comprehensive research perspective for educators, as well as help optimize the strategy of collaborative learning, and improve the learning effect.

2 SOCIAL NETWORK FEATURES OF COLLABORATIVE LEARNING COMMUNITY

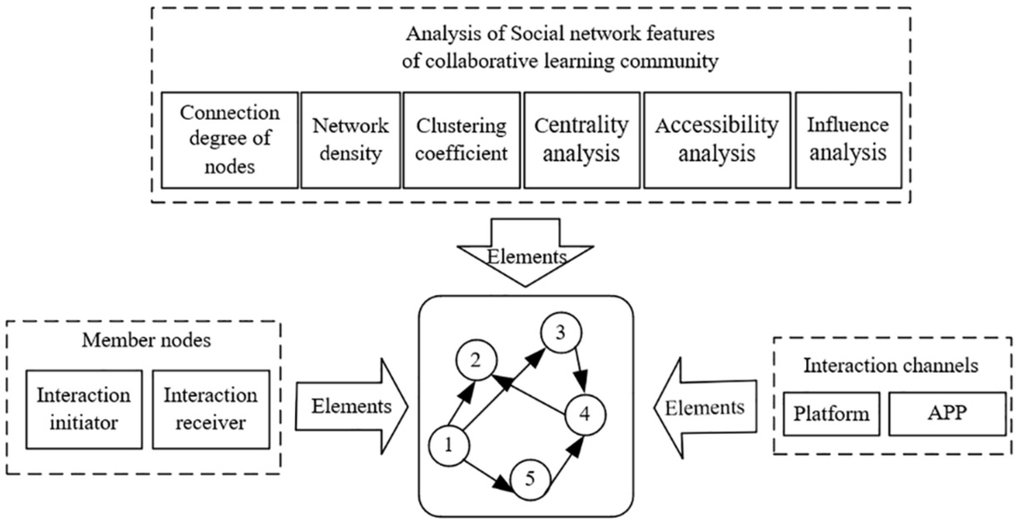

Fig. 1. Interaction data analysis model of collaborative learning community

In this study, a collaborative learning community is defined as a specific educational environment in which members (usually students) cooperate, communicate and share with each other in order to achieve their common learning goals. In such a community, learners are no longer passive recipients of knowledge, but actively participate in the process of knowledge creation and dissemination. Using the methods of social network analysis, the complex pattern of interactions among learners can be visualized. Every student is a unique node in this network and he or she forms specific relationships and connections with other students. These kinds of connections are not only related to the sharing of learning content, but involves multiple dimensions such as influence and the centrality of accessibility. Hence, a collaborative learning community is not just a learning group, but a social network structure full of dynamic interactions and influence transfer. Figure 1 illustrates the interaction data analysis model of collaborative learning community.

To gain a deeper understanding about interaction patterns and structural characteristics within a collaborative learning community. So as to get a more accurate knowledge about the relationship and interaction patterns of learners, this study chose three indicators (connection degree of nodes, network density, clustering coefficient) as metrics of social network feature parameters of a collaborative learning community.

A student with high connection degree may be a group leader, an active member, or a knowledge center. Students of this kind play important roles in the learning process, as they connect to multiple members and contribute to the transfer and sharing of knowledge. So, in this study, the connection degree of member nodes had been chosen as the metric to measure the number of connections between a single node and the other nodes, and this parameter reflects a student's interaction frequency and activity degree in the community.

To calculate the connection degree of member nodes, the first thing is to collect the data of interactions among learners. These data can come from the discussion boards of online learning platforms, the collaboration records of group projects, or the interaction logs of other forms. Then, the second step is to build a social network model in which each learner is a node and each interaction is represented by the edge between two nodes. Next, count the number of connections (edges) between a node (learner) and the other nodes, and this number represents the interaction frequency of this learner in the community. At last, rank the connection degrees of all nodes, identify the learner with the highest frequency, and figure out its importance and role in the learning community.

Assuming: each member node attains at least j hops node information, and the total number of member nodes is H, $j \leq H$. E_{fb} represents the connection degree of member node b with respect to member node f, e_{ub} represents the ratio of member node b that can be accessed to by member node f through u hops; m_{ub} represents the total number of times of the u-th hop of the current member node, m represents the number of times that the u-th hop node of the current member node is node b; during the information transfer process, when accessing to the current member node u, there are l hops to member node b, wherein m_{ulo} represents the number of paths of the o-th hop; when accessing to current node iu, $u11$ represents that member node b can be accessed to using one hop, then the calculation formula of the connection degree of member node b with respect to member node f is:

$$\begin{aligned} E_{fb} &= e_{1b} + e_{2b} + e_{3b} + \cdots + e_{jb} (1 \leq u \leq j) \\ &= \frac{m_{1b}}{m_1} + \sum_{m11}^{j11} \frac{m_{u11}}{m_1} \cdot \frac{m_{u11} \cdot m_{2n} b}{m_{u11} \cdot m_2} \\ &+ \sum_{u21}^{j21} \frac{m_{u21}}{m_1} \left(\sum_{u22}^{j22} \frac{m_{u21} \cdot m_{u22}}{m_{u21} \cdot m_2} \cdot \frac{m_{u21} \cdot m_{22} \cdot m_{3b}}{m_{u21} \cdot m_{22} \cdot m_{u3}} \right) \ldots\ldots \end{aligned} \quad (1)$$

Figure 2 below gives an example. Assuming the number of times of information transfer of f-1, f-2, and f-3 is 2, 3, and 1, respectively; and the number of times of information transfer among other member nodes is all 1. Then, it can be discovered that there are three paths to access to member node *b* from member node *f*, which are respectively *f*-1-7-*b*, *f*-2-6-*b*, and *f*-2-5-*b*. All paths from member node *f* to member node *b* are three hops, that is: $E_{fb} = e_{3b} = 0.5 + 0.05 + 0.03 = 0.58$.

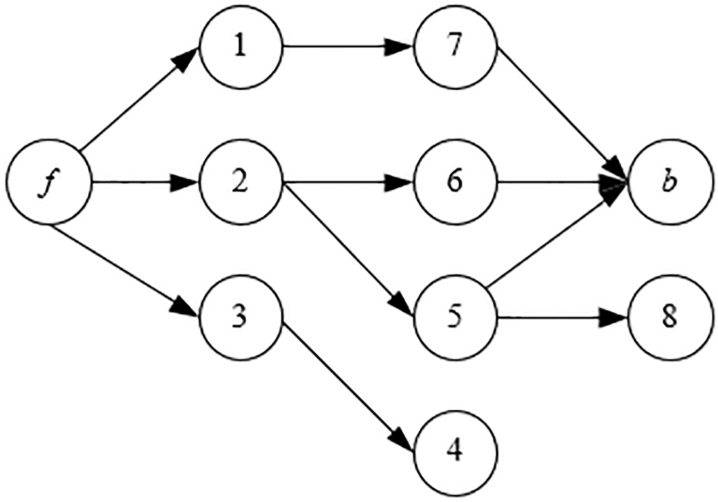

Fig. 2. An example of node connection degree calculation

If the constructed social network is an undirected graph, then $f_{uk} = f_{ku}$ and $f_{uk} = 0$. The above formula can be simplified to:

$$M = \frac{1}{B(B+1)} \sum_{u=1}^{B} \sum_{k=u+1}^{B} f_{uk} \tag{2}$$

A high-density collaborative learning community implies that there are more frequent and extensive interactions among learners, and such an environment is more conducive to deeper level knowledge sharing and discussion. Thus, in this paper, network density had been chosen as the metric to measure the proportion of connections that actually exist in all possible connections in the entire network, and this parameter can describe the overall activity and connectivity of the community. Network density is the ratio of the number of connections that actually exist in the network to the number of all possible connections. Assuming: B represents the total number of nodes, $[B(B-1)]/2$ represents the theoretical maximum value that can be reached by the number of edges in the undirected social network graph, R represents the number of edges that actually exist in the social network graph, then the calculation formula can be written as:

$$F = \frac{2R}{B(B-1)} \tag{3}$$

Through clustering coefficient, educators can detect whether there are small groups or isolated islands in the network. A learner with a high clustering coefficient may imply that the learner often interacts with a small group of learners, and seldom exchanges with others. In this study, clustering coefficient had been chosen as the metric to measure the connectivity between a node with its neighbors, and this parameter reflects whether a learner's interaction is within some certain small groups or circles. For each node (learner), the first thing is to identify all its neighbor nodes and calculate the number of connections that actually exist between it and the neighbor nodes. The clustering coefficient is the ratio of the number of connections that actually exist between nodes to the number of all possible connections. Assuming: $j_u(j_u - 1)/2$ represents the maximum number of edges existing between j_u nodes in a social network, L_u represents the number of edges that actually exist between j nodes, then formula $V_u = 2L_u/[j_u(j_{qu} - 1)]$ can be used to calculate the clustering coefficients of node individuals in a social network. The formula is:

$$V = \frac{1}{B}\sum_{u=1}^{B} V_u \tag{4}$$

3 ACCESSIBILITY ANALYSIS OF MEMBERS IN COLLABORATIVE LEARNING COMMUNITY

In this study, the accessibility of a collaborative learning community is defined as the connection degree that a current member node can access the target nodes within three hops during the process of information transfer. The reason for this definition is that in a real learning environment, information is not only transmitted directly from one student to another, but may also be transferred through multiple intermediate nodes, and the limit of three hops gives a reasonable distance to simulate information transfer in the learning community within a limited time range. Besides, in social network theory, it is believed that there is at most six degrees of separation between any two people, and in a learning community, this distance may be shorter because of the limited number of members and their common goal of collaboration. By setting this three-hop limit, the effect of such close network relevance can be better captured, and those nodes that work in indirect interactions but may be overlooked in direction interactions can be better understood. These intermediate nodes may play key roles in knowledge transfer, collaboration and learning dynamics. For these reasons, in this paper, the connection degree E_{fb} of member nodes had been slightly modified, and the formula is:

$$\begin{aligned} V_{fb} &= e_{1b} + e_{2b} + e_{3b} \\ &= \frac{m_{1b}}{m_1} + \sum\nolimits_{u=1}^{d} \frac{m_{1u}}{m_1} \cdot \frac{m_{1u} \cdot m_{2b}}{m_{1u} \cdot m_2} + \sum\nolimits_{k=1}^{s} \frac{m_{u21}}{m_1}\left(\sum\nolimits_{j=1}^{h} \frac{m_{1k} \cdot m_{2j}}{m_{1k} \cdot m_2} \cdot \frac{m_{1k} \cdot m_{2j} \cdot m_{3b}}{m_{1k} \cdot m_{2j} \cdot m_3}\right) \end{aligned} \tag{5}$$

The first hop of a member node refers to all nodes that directly connect to this node, when node b is contained in it, and m_1 is the total number of messages sent by node f. In a social network graph, select a current node and identify all nodes that are directly connected to it, and this can be completed by checking the neighbor list of the node or using a neighbor matrix. The attained result is a list of direct neighbors of the current node, and they are only one hop away from the current node. The number of times a member node f can access a member node b using one hop can be represented by m_{1b}.

The second hop of node f refers to all nodes that are not directly connected to the current node but are directly connected to its first-hop nodes. First, identify all first-hop nodes of the current node, then, find out their direct neighbors. Then, from the new neighbor list, remove the current node and all the nodes that are already included in the first-hop nodes, and the rest are the second-hop nodes. The attained result is a list of nodes that can be accessed from the current node using two hops. When node b is contained in it, the total number of access times of the second hop of node f can be represented by $m_{1u}m_2$, and the number of times that the node b is a second hop node of node f is represented by $m_{1u}m_{2b}$.

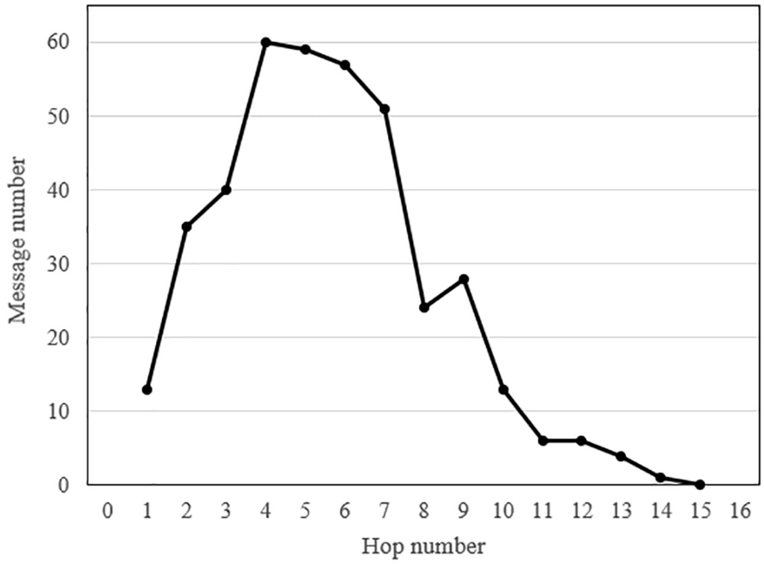

Fig. 3. Relationship between hop number and message number of the information transfer of member nodes

The third hop refers to all those nodes that are not directly connected to either the current node or its first-hop nodes, but are directly connected to its second-hop nodes. First, identify all second-hop nodes of the current node, and find out their direct neighbors. Then, from the new neighbor list, remove the current node, and all first-hop and second-hop nodes, and the rest are the third-hop nodes. The attained result is a list of nodes that can be accessed to from the current node through three hops. When node *b* is contained in it, in the current path, the number of access times of first hop of node *f* is represented by m_{1k}, the number of access times of second hop of node *f* is represented by $m_{1k}m_2$, the number of access times of third hop of node *f* is represented by $m_{1k}m_2m_3$, and the number of times that the node *b* is a third hop node of node *f* is represented by $m_{1k}m_2m_{3b}$. Figure 3 shows the relationship between hop number and message number of the information transfer of member nodes.

Based on the accessibility of member nodes, the purpose of classifying node-to-node relationships is to hierarchize the mutual influence and interaction frequency between nodes. Specifically, the node-to-node relationships can be categorized into four types: nodes with high repetition of first hop access, nodes with less first hop access or repeated second hop access, nodes with less second hop access or repeated third hop access, nodes with less third hop access or access to nodes with more than three hops.

Nodes with high repetition of first hop access: those that have direct and frequent contact with the target node. In the learning community, they have significant interdependence with the target node. That is, if $V_{fb} \geq m_1/r$, then member node *b* can be considered as a high accessibility node and is mainly of this type.

Nodes with less first hop access or repeated second hop access have direct contact with the target node, but the frequency is low, or they often contact the target node through an intermediate node. In a learning community, their influence is smaller than that of the first type nodes. If $m_1/r \geq V_{fb} \geq m_{1u} \cdot m_2/m_{1u}$, then it can be considered that node *b* is a high accessibility node of node *f* and is mainly of this type.

Nodes with less second hop access or repeated third hop access have no direct contact with the target node but they access the target node via 1–2 intermediate nodes. Their contact with the target node becomes indirect, but there are still some interactions and influence. If $m_{1u} \cdot m_2/m_{1u} \geq V_{fb} \geq m_{1u} \cdot m_2 \cdot m_3/m_{1u} \cdot m_{2j}$, then node b can be considered as an accessible node of node f and is mainly of this type.

Nodes with less third hop access or access to nodes with more than three hops only have sparse contact with the target node, and they have to establish connections with the target node through multiple intermediate nodes. In a learning community, their interdependence and influence with the target node is the lowest. If $m_{1u} \cdot m_2 \cdot m_3/m_{1u} \cdot m_{2j} \geq V_{fb}$, then node b can be considered as a low accessibility node of node f and is mainly of this type.

The specific classification process is:

1. Data collection: collect the interaction data between all member nodes within the learning community.
2. Build adjacency matrix: use the interaction data to establish an adjacency matrix that represents the intensity or frequency of connections between nodes.
3. Calculate the first hop, second hop, and third hop nodes of each node; as mentioned above, identify nodes that can be accessed from a node via one, two, and three hops.
4. Classification.
   – For each node, check its hop nodes; if the contact frequency reaches a predefined threshold, then classify these nodes as the "nodes with high repetition of first hop access".
   – Check those nodes that have low first hop contact frequency with the target node and those have repeated second hop contact with it, and classify them as the "nodes with less first hop access or repeated second hop access".
   – Check those nodes that have low second hop contact frequency with the target node and those have repeated third hop contact with it, and classify them as the "nodes with less second hop access or repeated third hop access".
   – Check those nodes that have low third hop contact frequency with the target node and those that access it using more than three hops, and classify them as the "nodes with less third hop access or access to nodes with more than three hops".

4 INFLUENCE ANALYSIS OF MEMBERS IN COLLABORATIVE LEARNING COMMUNITY

Influence is not only about the direct relationship of a member, but is related to its influence on other members and its position in the network. *Lead* index and accessibility centrality analysis provide a comprehensive perspective to capture these complex relationships. In a learning community, the dissemination of information, resources, and learning methods is very important. By analyzing the accessibility centrality of nodes, we can better figure out which nodes are playing key roles in the dissemination process. Therefore, in order to more accurately describe the importance and role of individuals in a learning community, in this paper, the *Lead* index and accessibility centrality analysis had been adopted to evaluate the influence of members in the collaborative learning community.

The *Lead* index is usually used to analyze the potential influence of individuals in social networks, and it needs to be based on some assumptions. At first, by default, it's considered that the influence of a node is not only determined by its direct contacts, but also by the connections of these contacts, and their farther connections. Second, a farther connection with the target node has a smaller contribution to the target node.

Third, the influence is recursive, meaning that the influence of a node partly depends on the influence of its neighbors. This paper defaults that the higher the reputation of a member node, the greater the value of its *Lead* index, and the reputation level is determined by the frequency of its interactions with other nodes, such as the number of times it is asked or it asks a question. Assuming: M_u represents the *Lead* index of node u, Y_u represents the number of times the node is asked, G_u represents the number of its replies, y_u represents the number of times the replies of node u being accepted, $y_u/(G_u - y_u)$ represents the ratio of the number of times the replies being accepted to the number of times the replies being rejected, W_u represents the number of times node u raises a question, γ represents the parameter of the *Lead* index, then there is:

$$M_u = \gamma \cdot Y_u \cdot \frac{Y_u}{W_u} \cdot \frac{G}{Y_u - G_u} \cdot \frac{y_u}{Y_u - y_u} = \frac{\gamma Y_u^2 G_u y_u}{W_u (Y_u - G_u)(Y_u - y_u)} \tag{6}$$

Based on the value of M_u and accessibility, the learning centrality of members in the collaborative learning community can be further defined. Assuming: M_k represents the *Lead* index of node k, V_{uk} represents the accessibility of nodes u and k, B represents the total number of nodes, then the definition is:

$$MC = \sum_{k=1}^{B-1} M_k V_{uk} \tag{7}$$

Accessibility centrality is a measure of a node's importance or centrality in the network, which reflects the interaction degree of a node to other nodes. In a collaborative learning community, it represents how a member interacts with other members to share and build knowledge. Assuming: FR_k represents the degree centrality of node k, f_k represents number of contact nodes of node k, H represents the total number of nodes, B represents the number of accessible nodes of node u, V_{uk} represents the accessibility of node k to node u, VC_u represents the accessibility centrality of node u, then there are:

$$FR_k = \frac{f_k}{H - 1} \tag{8}$$

$$VC_u = \sum_{k=1}^{B-1} V_{uk} FR_k \tag{9}$$

5 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Social network centralization of collaborative learning community at different stages

	Platform		*APP*		Overall	
	In-Degree Network Centralization	Out-Degree Network Centralization	In-Degree Network Centralization	Out-Degree Network Centralization	In-Degree Network Centralization	Out-Degree Network Centralization
Early stage	55.23%	25.48%	221.54%	85.16%	263.28%	124.15%
Mid stage	49.31%	32.56%	215.89%	326.95%	246.89%	367.16%
Late stage	52.36%	44.98%	268.26%	296.14%	326.15%	325.49%

Table 1 lists the statistical values of the social network centralization of collaborative learning community at different stages (early, mid, and late). According to the table, at all stages, for all kinds of platforms, the in-degree network centralization is higher than the out-degree network centralization, and this means that some members in the collaborative learning community receive information more frequently than send out information. Regardless of the stage, in-degree and out-degree network centralization of app platforms are far higher than those of the conventional platforms. This may be due to the fact that apps can provide more convenient interaction tools, which enables the information to spread more widely and deeply. At mid and late stages, the out-degree network centralization of apps exceeds 300%, which means that certain nodes (or members) play an above-average role in information dissemination.

According to the data, speaking overall, the in-degree and out-degree network centralization of late stage are higher than those of early and mid-stages, especially the in-degree network centralization rose from 263.28% to 326.15%, suggesting that with the passage of time, some members in the learning community become more important receivers of information. The out-degree network centralization of mid stage reached 367.16%, which is the highest value among the three stages. This may be related to certain key activities or projects at mid stage, which made some members more active in sharing information.

In summary, some members of the collaborative learning community are more active in receiving information, which is reflected as high in-degree network centralization. Apps can create more active and wider environments for the interactions of learning communities, especially in the aspect of information sharing. Over time, the centrality of some members in the community increased constantly during information interaction, which may be related to their increasingly important roles in the learning community. At mid stage, there might be some key activities or factors that made information sharing hit the peak.

Table 2. Statistics of repeated concurrences of first hop nodes of member nodes

Member Node No.	Number of Delivered Messages	First Hop Node	Number of Occurrences	Member Node No.	Number of Delivered Messages	First Hop Node	Number of Occurrences
*S*0	4	*S*2	2	*S*2	6	*S*13	4
*S*3	5	*S*4	3	*S*4	6	*S*0	4
*S*6	2	*S*94	2	*S*11	4	*S*47	4
*S*13	3	*S*15	2	*S*12	5	*S*16	4
*S*24	6	*S*21	2	*S*71	4	*S*92	2
*S*42	8	*S*92	2	*S*43	3	*S*45	2
*S*46	5	*S*94	3	*S*47	4	*S*85	2
*S*52	6	*S*60	4	*S*51	4	*S*38	2
*S*55	4	*S*1	2	*S*50	7	*S*63	2
*S*56	2	*S*19	2	*S*42	4	*S*15	2
*S*74	3	*S*84	4	*S*77	4	*S*88	2
*S*79	5	*S*96	2	*S*30	3	*S*84	2
*S*41	5	*S*52	3	*S*84	6	*S*13	2
*S*96	4	*S*84	3	*S*86	4	*S*60	2
*S*90	5	*S*89	3	*S*87	5	*S*31	3

Table 2 lists the repeated concurrences of first hop node of different member nodes in the social network of collaborative learning community. Each member node has its corresponding number of delivered messages, first hop node, and number of occurrences. According to the data in the table, it's observed that, when a member node acts as an information source (such as *S*0, *S*3, *S*6), the number of occurrences of its first hop node (such as *S*2, *S*4, *S*94) is higher, indicating that for some member nodes, their choice of first hop node is relatively fixed rather than random. For some member nodes (such as *S*42, *S*46, *S*52), the number of delivered messages is large, but the number of repeated occurrences of their first hop node doesn't increase significantly, suggesting that although these member nodes are active in the social network, their relationship with the first hop node may not be particularly close, or they have multiple commonly-used first hop nodes.

As mentioned earlier, in case of identical member nodes, the repetition of first hop node is high. For example, for member node *S*0, its first hop node *S*2 is repeated 2 times; as for member node *S*4, its first hop node *S*0 is repeated 4 times. This implies that during the process of information transmission, the path of first hop is usually stable, and this stability may be based on a variety of factors, such as the social relationship, learning similarity, or other common characteristics between two members.

Therefore, in the social network of collaborative learning community, for some member nodes, the choice of first hop node is usually fixed and stable rather than random. Although some member nodes are quite active in the network, this does not mean that they must have a higher repetition rate of first hop node. The path stability of first hop may stem from a closer relationship between two members or their common characteristics, which provides an important clue for educators about the interactions between learners and their learning habits. This phenomenon of stability also implies that when designing or intervening the education strategies, attention must be paid on how to use and consolidate such stable learning relationship.

Table 3. Statistics of repeated concurrences of second hop nodes of member nodes

Member Node No.	Number of Delivered Messages	Second Hop Node	Number of Occurrences	Member Node No.	Number of Delivered Messages	Second Hop Node	Number of Occurrences
*S*2	6	*S*15	2	*S*32	7	*S*25	2
*S*4	6	*S*13	3	*S*33	3	*S*12	2
*S*5	5	*S*94	3	*S*37	8	*S*12	2
*S*6	5	*S*46	2	*S*39	3	*S*46	2
*S*8	5	*S*82	2	*S*59	7	*S*65	2
*S*9	8	*S*51	3	*S*61	4	*S*90	2
*S*11	4	*S*35	2	*S*67	7	*S*14	2
*S*12	5	*S*15	2	*S*68	6	*S*72	2
*S*14	10	*S*13	2	*S*71	4	*S*27	2
*S*17	6	*S*12	3	*S*74	3	*S*55	2
*S*18	3	*S*15	2	*S*79	5	*S*4	4
*S*20	4	*S*70	2	*S*82	8	*S*43	4
*S*21	8	*S*48	3	*S*84	6	*S*13	2
*S*24	6	*S*84	2	*S*90	5	*S*15	2
*S*29	5	*S*12	2	*S*96	4	*S*60	2

Table 3 lists the repeated concurrences of the second hop nodes of different member nodes in the social network of collaborative learning community. Each member node has its corresponding number of delivered messages, second hop node, and number of occurrences. According to data in the table, it's observed that, when a member node acts as an information source (such as *S*2, *S*4, *S*5), their second hop nodes (such as *S*15, *S*13, *S*94) showed a high repetition rate, indicating that when delivering the messages, the path of second hop is also relatively stable. For some member nodes (such as *S*14, *S*9, *S*21), the number of delivered messages is high, but this doesn't necessarily mean that the repetition rate of their second hop nodes is very high. Although these nodes are active in the network, the path of their second hop might be diverse or shared with other member nodes. According to the data, taking *S*4 for instance, its second hop node *S*13 is repeated 3 times, which means that in most cases, the transfer of information from *S*4 to *S*13 is carried out through a fixed intermediate node. This stability may be based on factors such as the close relationship between the two nodes, or their common interests or learning goals.

Thus, in a social network of collaborative learning community, similar to the path of first hop, the path of second hop also exhibited a relative stability. For some member nodes, the choice of second hop node is usually fixed. Although some member nodes are highly active in the social network, this doesn't necessarily lead to an increase in the repetition number of their second hop nodes, probably because these nodes have close connections to other nodes. The path stability of second hop proved that, when designing collaborative learning strategies or conducting learning interactions, educators can consider these stable paths to enhance the effect of collaboration and interaction among learners.

Table 4. Statistics of repeated concurrences of third hop nodes of member nodes

Member Node No.	Number of Delivered Messages	Second Hop Node	Number of Occurrences	Member Node No.	Number of Delivered Messages	Second Hop Node	Number of Occurrences
*S*0	4	*S*15	2	*S*27	9	*S*56	2
*S*5	5	*S*40	1	*S*32	7	*S*1	2
*S*8	5	*S*15	2	*S*37	8	*S*4	2
*S*14	10	*S*15	2	*S*69	6	*S*82	1
*S*24	6	*S*40	1	*S*90	5	*S*73	2

Table 4 gives the statistics of repeated counts of third hop nodes of each member node in the social network of collaborative learning community. According to the table, compared with first hop and second hop nodes, the repetition rate of third hop nodes is obviously lower. For example, the third hop node *S*40 of node *S*5 appeared only once, and the hop node *S*40 of node *S*24 appeared only once as well. In contrast to our observation of first hop and second hop nodes, the path of third hop has a higher degree of randomness. For those highly active nodes, such as *S*14, the repetition rate of its third hop node *S*15 is not high, implying that although some nodes are highly active in the social network, their third hop path may be shared by multiple member nodes. When it gets deeper into the third hop or even deeper nodes, the randomness of path would increase, and this may be due to the fact that with the increase of hop number, the node number, and path possibility, the messages pass through would increase accordingly. Therefore, in the study of overall connection degree, the connection degree of nodes of more than four hops may diminish gradually, and the analysis of these deeper hops will bring more noise rather than help us better understand the core dynamics of social networks.

Thus, in the social network of collaborative learning community, the path of third hop shows a higher degree of randomness. Although some nodes may be very active in the network, their choice of third hop nodes tends to be diverse. Compared with first hop and second hop paths, the path of third hop is more random, indicating that when a message is to be delivered to a farther node, the selection of path might be affected by more factors. Analyzing the connection degree of nodes farther than four hops won't give us more insights, but will introduce more noise due to the increasing path randomness as the hop number increases.

Table 5. Ratios of interaction content of collaborative learning community at different stages

	Phase	Platform	*APP*	Overall
Early stage	First acquaintance	69.23%	67.15%	66.38%
	Establish basic connections	13.15%	15.23%	15.89%
	Content sharing	11.69%	13.36%	12.46%
	Group activity	4.96%	3.15%	3.62%
	Discussion and interaction deepening	4.58%	3%	3.3%
Mid stage	Learning interaction deepening	66.39%	62.31%	61.59%
	Multi-direction exploration	12.48%	15.28%	15.29%
	Group creation	12.87%	12.81%	11.69%
	Group reflection	3.81%	3.24%	3.28%
	Integrate resources	4.15%	5.89%	6.62%
Late stage	Learning summary	67.15%	62.89%	61.49%
	Knowledge recreation	13.2%	13.26%	14.26%
	Extension and expansion	12.8%	13.54%	12.59%
	Consolidate community structure	4.12%	4.38%	5.16%
	Inheritance and guidance	4.12%	6.53%	5.81%

Table 5 lists the ratios of interaction content of the collaborative learning community at different stages. At the early stage, regardless of conventional platform, app, or speaking overall, the first acquaintance phase is the main content of early stage interactions, and the ratios are all over 66%. This means that members were getting to know each other and establishing initial connections during this phase. The ratios of establishing basic connections and content sharing are lower, reflecting the basic interactions and sharing behaviors of members after acquaintance. The ratios of the phase of group activity and discussion and interaction deepening are the lowest, suggesting that at the early stage, members of the learning community hadn't conducted deep discussions or group activities yet.

At the mid stage, the ratio of the learning interaction deepening phase is still the highest, but it declined a bit compared with the early stage, indicating that with the deepening of learning, other interaction forms had begun to increase. The ratios of multi-directional exploration and group creation phases are all between 12% and 15%, indicating that the learning community began to try various strategies and collective creation activities. The ratio of resource integration phase is slightly higher than the early stage, showing that with the deepening of learning, members began to share and integrate resources more often. The ratio of group reflection phase is relatively low, but it is still higher than at the early stage.

At the late stage, although the ratio of learning summary is still the highest, it decreased a bit compared with early and mid-stages, showing that the learning community began to change to other interaction forms. The ratios of knowledge recreation and extension and expansion are all between 12% and 14%, suggesting that the members interacted more about knowledge recreation and learning extension. The ratios of the phases of community structure consolidation and inheritance and guidance both increased, especially the phase of inheritance and guidance. Its ratio reached 6.53% on apps, indicating an increase in the maturity of the learning community and the inheritance activities.

Thus, the collaborative learning community exhibited obvious trends in interaction content at different stages. Early stage is mainly first acquaintance, mid stage is mainly multi-directional exploration and group creation, and late stage is mainly learning summary and knowledge recreation. With the deepening of learning, activities such as group reflection, resource integration, and inheritance and guidance gradually increased, indicating that during the growing process of the learning community from formulation, development, to maturity, the interaction pattern and content of members are evolving and deepening constantly.

6 CONCLUSION

This study investigated the social network characteristics of collaborative learning communities. At first, relevant parameters were measured and calculated, the accessibility of members in the collaborative learning community was analyzed, and the influence of these members in the community was discussed based on the *Lead* index and the accessibility centrality of member nodes. The statistics of degree centrality show that the connection method of nodes in the community exhibit different patterns at different stages. The network centralization is higher at early and late stages and lower at mid stage, implying a more decentralized interaction pattern during the mid stage. Statistics of repeated counts of nodes show that, the repetition rates of first hop and second hop nodes are higher, indicating that the path of information transmission during the first two hops is relatively stable; while in the third hop, the randomness of the path increases. The ratios of interaction contents show that at different stages, the focus of member interactions would change and deepen from the first acquaintance and basic interactions to deeper interactions and knowledge innovation.

This study discovered that the social network interaction behaviors in collaborative learning community have different features and patterns at different learning stages. From the simple interaction at early stage to the deep-level cooperation at mid and late stages, members in the learning community would adjust their interaction method and content constantly. The social network analysis provides a powerful tool to help us gain a deeper understanding of the structure and dynamics of these interactions, offering valuable insights for optimizing collaborative learning strategies and methods.

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8 AUTHORS

Chunling Ren is a counselor at the School of Electrical Engineering, Changzhou Vocational Institute of Mechatronic Technology. She holds the qualification of a Level 3 Psychological Counselor certified by the Chinese government, as well as being a Level 3 National University Student Career Planning Advisor. Her research focuses on the psychological development and counseling of college students (E-mail: v.bin@163.com; ORCID: https://orcid.org/0009-0006-9784-4702).

Zheng Qi is the head of the Environmental Art Design program at the School of Creative Design, Changzhou Vocational Institute of Mechatronic Technology. She is a member of the Jiangsu Province Building Decoration Association, and her research interests encompass interior design and the preservation of historical architectural heritage (E-mail: qixiaozheng@163.com; ORCID: https://orcid.org/0009-0007-5759-8225).