Evaluation of the Effectiveness of Hybrid Learning Activities Based on a Learning Community Network

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Abstract—Hybrid Learning Community Network (HLCN) can link individuals to collectives systematically, support both virtual and actual scenarios, and share and trade knowledge, experience, and learning resources. Existing studies on HLCN are mostly theoretical research, there're very few empirical evidences, and the integrity of the research systems is yet to be improved further. In view of these shortcomings, this paper proposed a theoretical model for HLCN and built an Evaluation Index System (EIS) for assessing the effectiveness of the hybrid learning activities and analyzing the feature parameters and centrality of the HLCN. Then in the paper, a Hybrid Learning Interactive Activity Content Network Relation (HL-IAC-NR) matrix was established based on learning community, and the indexes such as students' learning attention on knowledge points and their learning sentiments were attained. At last, this paper used the Charnes-Cooper-Rhodes (CCR) model in Data Envelope Analysis (DEA) to evaluate the relative effectiveness, and the real-time effects of different types of hybrid learning interactive activities were analyzed. The effectiveness of the proposed model and evaluation method was verified via experiments.

Keywords—hybrid learning, learning community, effectiveness evaluation, interactive activities

1 Introduction

Although online learning can provide richer learning resources and more flexible learning methods, for reluctant students with poor consciousness and initiative, it's hard to get ideal learning effects [1–8]; as for independent students who learn by themselves, it's hard to enhance their learning abilities [9–13]. So, in order to give full play to the real effects of hybrid learning, Hybrid Learning Community Network (HLCN) could be built to integrate online and offline learning and form hybrid learning network communities [14–17]. HLCN can link individuals to collectives systematically, support both virtual and actual scenarios, and share and trade knowledge, experience, and learning resources [18–21]. Forming learning communities with common group learning goals based on the learning community theory and exploring innovative hybrid teaching modes are of great significance for the knowledge sharing and innovation of HLCN.

Herodotou et al. [22] argued that the learning community and citizen science in online environment can be regarded as a means for young people to participate in and contribute to the real science, to prove their viewpoint, they analyzed 34 depth interviews and log files of several young people respondents aged between 11 and 19 who had participated in a citizen science project hosted on the platform Zooniverse. Regarding the importance of the sense of learning community in online education, field scholars emphasized its influence from different perspectives, for instance, Zhao et al. [23] believe that an ideal learning community can compensate for the shortcoming in technical performance to some extent, and it can increase the attractiveness of online learning systems and help learners adopt them and continue to use them. Forming online English learning communities on the exploratory learning community framework is an effective way to solve problems existing in college English teaching in China, so scholars Liao and Tian [24] took Wechat groups and Xiaodaka mini-program as platforms, followed the theoretical guidelines of social presence, cognitive presence and teaching presence of the Community of Inquiry, and discussed the feasibility and practicability of building such online English learning communities. The urban and rural online communities can share high-quality educational resources, however, existing relevant studies mainly focused on the building of urban and rural online teaching communities for teachers, few have concerned about building urban and rural online learning communities for students or the teaching/learning communities for both teachers and students. Li [25] used the Moodle platform to create urban and rural online learning communities for students and realized the joint construction of teacher-teacher, student-student, and teacher-student communities, which had promoted the sharing of urban and rural educational resources. Duan and Wang [26] aimed at the construction of online learning community of Advanced English Course, which is a new approach of practicing the distant learning thoughts and further boosting online education. They started with the definition of learning community, introduced the process of constructing online learning communities, and pointed out the difficulties, advantages, disadvantages and countermeasures from the perspective of construction effectiveness of online learning communities.

After reviewing existing literatures of world field scholars, it's found that the current studies on related topics generally lack of discussions on the hybrid learning environment, although they have revealed some features of learning communities, they are mostly theoretical research, there're very few empirical evidences, and the integrity of the research systems is yet to be improved further. In view of these shortcomings, this paper studied the evaluation of the effectiveness of hybrid learning activities based learning community. In the second chapter, this paper proposed a theoretical model for HLCN and built an EIS for assessing the effectiveness of the hybrid learning activities and analyzing the feature parameters and centrality of the HLCN. In the third chapter, this paper built a HL-IAC-NR matrix based on learning community, and attained the indexes such as students' learning attention on knowledge points and their learning sentiments. In the fourth chapter, this paper used the CCR model in DEA to evaluate the relative effectiveness, and analyzed the real-time effects of different types of hybrid learning interactive activities. At last, the effectiveness of the proposed model and evaluation method was verified via experiments.

2 Feature parameters and centrality of the HLCN

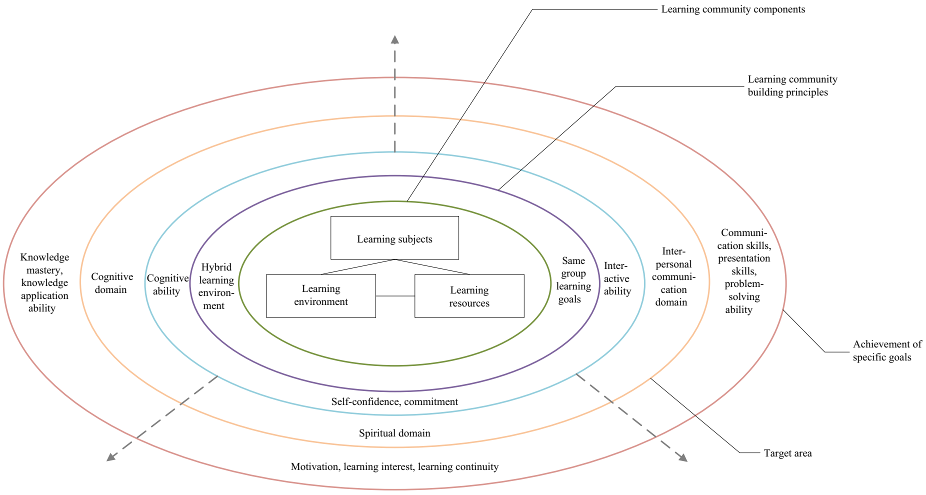

Fig. 1. HLCN model for hybrid learning activities

This paper took the learning community theory and the features of hybrid teaching as theoretical basis to construct the HLCN model, as shown in Figure 1. The core layer of the model is consisted of three aspects of HLCN, namely the learning subjects, the learning environment, and the learning resources; the second layer of the model is the learning community building principles, namely the same hybrid learning environment, and same group learning goals. Then, the target area of HLCN is given, that is, to deepen and optimize the student individuals and groups in terms of cognitive domain, spiritual domain, and interpersonal communication domain. At last, the achievement of specific goals of the network includes several aspects, including the knowledge mastery, knowledge application ability, learning initiative, learning interest, learning continuity, communication skills, presentation skills, and problem-solving ability.

To evaluate the effectiveness of hybrid learning activities based on learning community, this paper built an EIS, as shown in Figure 2, five indexes representing the attributes of the HLCN and two indexes represents the features of the interactive activity content of hybrid learning were selected to form the EIS, which was then subject to DEA.

At first, this paper analyzed the constructed HLCN, and the specific feature parameters of the network include the average path length, network density, and clustering coefficient, their detailed introductions are given below:

Assuming: K represents the average path length that measures the average degree of separation between learning subject nodes in the HLCN, namely the average distance between all learning subject node pairs; M represents the number of learning subject nodes in the HLCN; M_c represents the learning subject node pairs; c_{ij} represents the shortest distance between two learning subject nodes, then the calculation formula of K is:

$$K = \frac{1}{M^2}\sum_{j=1}^{M}\sum_{i=1}^{M} c_{ij} \tag{1}$$

Then, the average path lengths between all the learning subject node pairs in the HLCN were summed, and the result was divided by the common learning subject node pairs in the network to attain the average path length of all learning subject node pairs. As for the graph of the HLCN, there are $c_{ij} = c_{ji}$ and $c_{ii} = 0$, then the following formula gives the simplified form of the above formula:

$$SW = \frac{2}{M(M-1)}\sum_{i=1}^{M}\sum_{j=i+1}^{M} c_{ij} \tag{2}$$

SW can be used to judge whether a HLCN has a small world effect or not. Many actual HLCNs contain a large number of learning subject nodes, but the average path length is very small, which would cause the small world effect.

Assuming: *C* represents the network density that measures the degree of interconnection between members in the HLCN, and its value can be attained by calculating the ratio of the actual number of connection edges between learning subject nodes in the HLCN and the possible largest number of connection edges. The closer the value of *C* is to 1, the tighter the connection between learning subject nodes; assuming *M* represents the total number of learning subject nodes in the HLCN graph; $[MM(M - 1)]/2$ represents the possible largest number of connection edges in the HLCN graph; *O* represents the actual number of edges in the HLCN graph, then the calculation formula of *C* is:

$$C = \frac{2O}{M(M-1)} \tag{3}$$

Assuming: *D* represents the clustering coefficient of the network that measures the aggregation of learning subject nodes in the HLCN, its value can be attained by calculating the average clustering coefficient of all individual learning subject nodes. Before calculating *D*, the individual clustering coefficients of each learning subject node should be calculated, which can be attained by calculating the ratio of the actual number of edges to the maximum number of edges between a learning subject node and other nodes that are directly connected to it. Assuming l_i represents the number of other nodes that are directly connected to a learning subject node; $l_i (l_i - 1)/2$ represents the maximum number of connection edges existing between the l_i learning subject nodes; N_i represents the actual number of connection edges existing between the l_i learning subject nodes; then the individual clustering coefficient of learning subject nodes in the HLCN could be calculated as $D_i = 2 N_i/[l_i(l_i - 1)]$, then, by dividing the sum of D_i by the number of learning subject nodes, *D* could be attained, and the calculation formula of *D* is:

$$D = \frac{1}{M}\sum_{i=1}^{M} D_i \tag{4}$$

Secondly, this paper analyzed the centrality of the HLCN. In HLCNs with different scales, the size of the absolute degree centrality is affected by the scale of the network, which can directly lead to inaccurate judgement of the core influence of the learning subject nodes. Therefore, this paper used the degree centrality to measure the kernel degree of learning subject nodes. Assuming l represents the absolute degree centrality of learning subject nodes; M represents the number of learning subject nodes in the HLCN graph, then the calculation formula of the degree centrality is:

$$D'_{RDi} = \frac{l}{M-1} \tag{5}$$

To figure out whether a learning subject node can affect the connection with other node pairs, this paper introduced the betweenness centrality to measure the ability of a learning subject node to affect the connection with other node pairs. If a learning subject node has a high probability of being on the connection edge of a learning subject node pair, then it indicates that this node plays an intermediary role in the connection between this node pair. Assuming: j and l represent two learning subject nodes; $H_{jl}(i)$ represents the number of times the learning subject node i appears on the connection edge between j and l; H_{jl} represents the number of connection edges existing between j and l, then the probability $T_{jl}(i)$ that a learning subject node appears on the connection edge of a learning subject node pair could be calculated using the following formula:

$$T_{jl}(i) = \frac{H_{jl}(i)}{H_{jl}} \tag{6}$$

The absolute betweenness centrality of node i is the result of the superposition of the betweenness degrees of all node pairs in the network, $j \neq l \neq i$, and in case of $j < l$, the absolute betweenness centrality of node i can be calculated by the following formula:

$$D_{XYi} = \sum_{j}^{M} \sum_{k}^{M} T_{jl}(i) \tag{7}$$

In case that the HLCN is a star-shaped network, then the relative betweenness centrality of node i can be calculated by the following formula:

$$D_{RBi} = \frac{2D_{RBi}}{m^2 - 3m + 2} \tag{8}$$

Assuming: c_{ij} represents the connection edge distance between learning subject nodes i and j, the following formula can calculate the absolute closeness centrality of a learning subject node, namely the sum of distances between this node and all other nodes in the network:

$$D_{APi}^{-1} = \sum_{j=1}^{M} c_{ij} \tag{9}$$

The smaller the closeness centrality of a learning subject node, the shorter the distance between this node and other nodes, and the higher the kernel position of this node in the entire HLCN, the following formula gives the calculation formula of relative closeness centrality:

$$D_{RPi}^{-1} = \frac{M-1}{D_{APi}^{-1}} \tag{10}$$

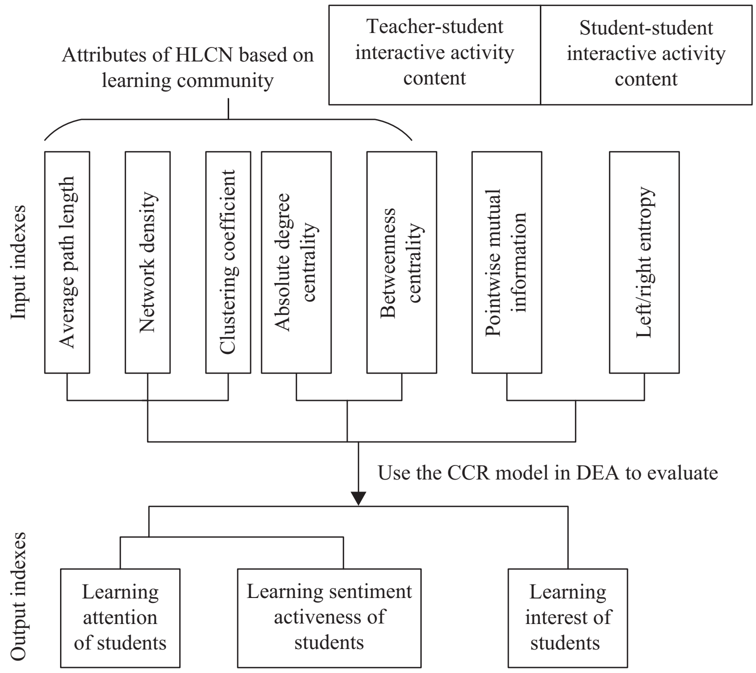

Fig. 2. EIS for assessing the effectiveness of hybrid learning activities

3 Construction of the HL-IAC-NR matrix

In order to evaluate the effectiveness of hybrid learning activities based on learning community, this paper constructed a HL-IAC-NR matrix based on learning community. In the paper, effective information was extracted from the data records of the teacher-student and student-student interactive behaviors of online learning platforms, and finally a 2D matrix of the keywords in course discussion, knowledge Q&A and other interactive content information was established. Key steps in constructing this matrix are the discovery of new words and the extraction of keywords based on word division. Assuming: $GR(a,b)$ represents the probability of two words appearing together; and $GR(a)$ represents the probability of one word appearing alone, then the pointwise mutual information was calculated in this paper to attained the representation of the cohesion of two words:

$$PMI(a,b) = log_2 \frac{GR(a,b)}{GR(a)GR(b)} \tag{11}$$

In order to accurately represent the degree of freedom of preselected words, this paper introduced the left/right entropy as the parameter, which can be defined by the following formula:

$$O_K(Q) = -\sum_{\forall x \subseteq X} T(xQ|)log_2 T(xQ|Q) \tag{12}$$

This paper used the software SATI to build this HL-IAC-NR matrix, but the keywords need to subject to the EndNote format conversion. Because the HL-IAC-NR matrix proposed in this paper is a matrix of equal rows and columns, assuming $a_{i,j}$ represents the number of times the learning subject node in the *i*-th row and the learning subject node in the *j*-th column appearing at the same time, by taking it as the elements of the matrix, the following matrix can be built:

$$X_{i,j} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,j} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,j} \\ \cdots & \cdots & \cdots & \cdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,j} \end{bmatrix} \tag{13}$$

Because the HLCN studied in this paper is undirected, the matrix elements $a_{i,j}$ are symmetrically equal about the diagonal. Key words in the matrix represent the key words of topics in the interactive activity content of hybrid learning based on learning community, they can represent a knowledge point or a learning sentiment, etc.

4 Methodology of the effectiveness evaluation of hybrid learning interactive activities

Based on the constructed HL-IAC-NR matrix, students' learning attention on knowledge points and their learning sentiments could be attained. The higher the learning attention degree of students on the knowledge points, the more positive their learning sentiment is, and this indicates that their hybrid learning interactive activities are more effective. In order to accurately evaluate the effectiveness of the hybrid learning interactive activities, this paper employed the CCR model in DEA to perform relative effectiveness evaluation and analyze the real-time effects of different types of hybrid learning interactive activities.

Assuming: there're m decision-making units (DMU) to be evaluated in the effectiveness evaluation of hybrid learning interactive activities, wherein each DMU has 1 input items and r output items independently, namely the influencing factors and the evaluation indexes. Assuming f_t^* represents the effectiveness evaluation of the *t*-th decision unit DMU_t, then its effectiveness value can be calculated by the following formula:

$$\begin{aligned} & f_t^* = Max \frac{\sum_{i=1}^{r} v_s b_{st}}{\sum_{i=1}^{l} u_i a_{it}} \quad \frac{\sum_{s=1}^{r} v_s b_{sj}}{\sum_{i=1}^{l} u_i a_{ij}} \leq 1 \\ & s.t. \quad u_i \geq \sigma > 0, i = 1, 2, ..., l \\ & v_s \geq \sigma > 0, s = 1, 2, ..., r \\ & j = 1, 2, ..., m \end{aligned} \tag{14}$$

Above formula was subjected to the conversion of linear programming, then there are:

$$\begin{aligned} & Maxh_t^* = \sum_{s=1}^{r} v_s b_{st} \\ & \sum_{i=1}^{l} u_i a_{it} = 1, j = 1, 2, ..., m \\ & s.t. \quad \sum_{s=1}^{r} v_s b_{sj} - \sum_{i=1}^{l} u_i a_{ij} \leq 0 \\ & u_i \geq \sigma > 0, i = 1, 2, ..., l \quad v_s \geq \sigma > 0, s = 1, 2, ..., r \end{aligned} \tag{15}$$

Assuming: R_{it}^- and R_{it}^+ are relaxation variables, they were introduced to perform the conversion of dual programming, then there are:

$$\begin{aligned} & Minh_t^* = \varphi_t - \sigma\left(\sum_{i=1}^{l} r_{it}^- + \sum_{s=1}^{r} r_{st}^+\right) \\ & \sum_{j=1}^{m} \phi_j a_{ij} + r_{it}^- = \varphi a_{it} \\ & \sum_{j=1}^{m} \phi_j a_{ij} - r_{st}^+ = b_{st} \\ & s.t. \quad \phi_j \geq 0, j = 1, 2, ..., m \\ & r_{im}^- \geq 0, r_{st}^+ \geq 0 \\ & i = 1, 2, ..., l, s = 1, 2, ..., r \end{aligned} \tag{16}$$

In above formula, ϕ represents the effectiveness coefficient and it satisfies $0 \leq \phi \leq 1$; r^- and r^+ respectively represent the input and output relaxation variables; φ represents the DMU combinations; the optimal solution of the effectiveness evaluation problem of hybrid learning interactive activities is φ, ϕ, r_t^-, r_t^+. When ϕ is equal to 1 and s_p^- and s_p^+ are both 0, then the DEA of DMU_t is effective, which means that there's no input redundancy or insufficient output in the DMU. When ϕ is less than 1, then the DEA of DMU_t is not effective, and effectiveness evaluation could be conducted on it. If $\Sigma_{j=1}^{m}\varphi_{jt}/\phi$ is less than 1, then the effectiveness of DMU_t will increase; if $\Sigma_{j=1}^{m}\varphi_{jt}/\phi$ is equal to 1, the effectiveness of DMU_t will not change; if $\Sigma_{j=1}^{m}\varphi_{jt}/\phi$ is greater than 1, then the effectiveness of DMU_t will decrease.

5 Experimental results and analysis

Table 1. Correlation analysis results

		Learning Attention	Sentiment Activeness	Learning Interest
Average path length	Correlation coefficient	0.748*	0.781*	0.841*
	P-value	0.021	0.053	0.069
Network density	Correlation coefficient	0.648*	0.694*	0.738*
	P-value	0.036	0.044	0.058
Clustering coefficient	Correlation coefficient	0.769*	0.738*	0.739*
	P-value	0.051	0.054	0.027
Absolute degree centrality	Correlation coefficient	0.784**	0.719*	0.831
	P-value	0.037	0.057	0.035
Betweenness centrality	Correlation coefficient	0.516*	0.825*	0.724**
	P-value	0.037	0.027	0.047
Pairwise mutual information	Correlation coefficient	0.629*	0.658*	0.586*
	P-value	0.052	0.126	0.027
Left/right entropy	Correlation coefficient	0.674*	0.704*	0.559*
	P-value	0.048	0.004	0.072

Notes: $^*P < 0.05$, $^{**}P < 0.01$.

Table 1 shows the results of correlation analysis on the effectiveness evaluation of hybrid learning interactive activities. As can be seen from the table, the Pearson correlation values are all greater than 0, indicating that there is a significant positive correlation between the input and output items of the evaluation. Learning attention and sentiment activeness are the prerequisites for better carrying out hybrid learning. Only when students participate in hybrid learning actively and with positive sentiments, can their learning be persistent and effective. Both teacher-student and student-student interaction activities need to be based on learning attention and sentiment activeness to cultivate students' communication ability, expression ability, and interpersonal skills.

Figure 3 shows the distribution of degree centrality. The horizontal and vertical coordinates of the graph are respectively the degree centrality and its corresponding probability.

As can be seen from the figure, R^2 value of curve fitting is 0.7921, indicating the curve is well fitted. According to the shape of the curve, it can be judged that the distribution of the degree centrality of the HLCN conforms to the power law distribution, on the whole, the constructed network is a scale-free network. Only a few learning subject nodes have many neighborhood nodes. In the constructed network, learning subject nodes with a degree centrality greater than 10 account for more than 6.5% of all nodes in the network, and these nodes have a greater influence. If some of these nodes have been ignored, then it will have a great influence on the implementation of the hybrid learning activities. Therefore, it is necessary to pay attention and process the content of the hybrid learning interactive activities participated by these 6.5% learning subject nodes to attain accurate effectiveness evaluation results of hybrid learning interactive activities based on learning community.

Figure 4 shows the distribution of closeness centrality. The horizontal and vertical coordinates of the graph are respectively the relative closeness centrality and its corresponding probability and frequency. According to the figure, we can see than the distributions of the probability and frequency of relative closeness centrality are close to the state of normal distribution, they are lower on both sides and higher in the middle. The relative closeness centrality distributes higher around 34, 35, and 36, accounting for more than 88% of the total network, and the lower values of relative closeness centrality account for less than 4% of the network. According to the experimental results, the values of the relative closeness centrality of the HLCN are generally low, indicating that the learning subject nodes in the network are closely connected. A small number of nodes have a stronger ability to connect to other nodes, and these nodes are the main subjects of hybrid learning interactive activities that require special attention.

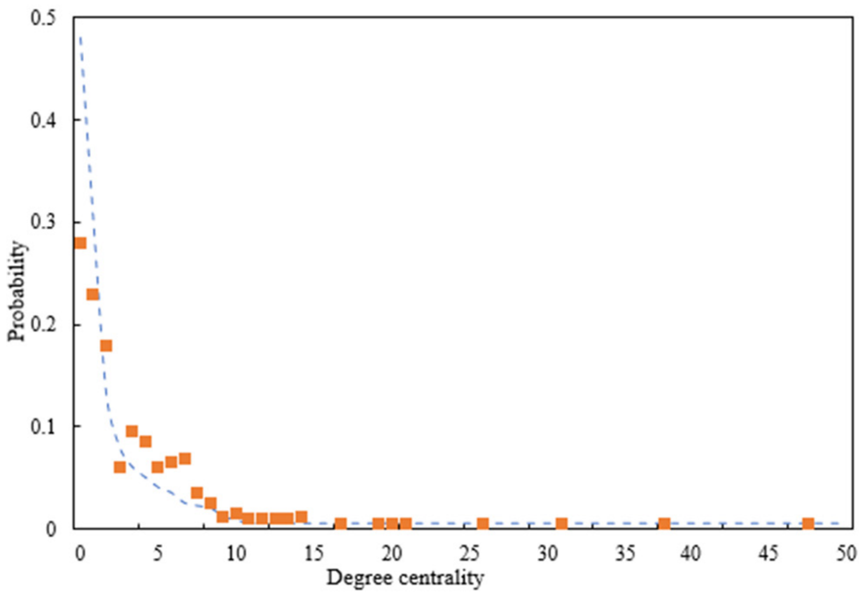

Fig. 3. Distribution of degree centrality

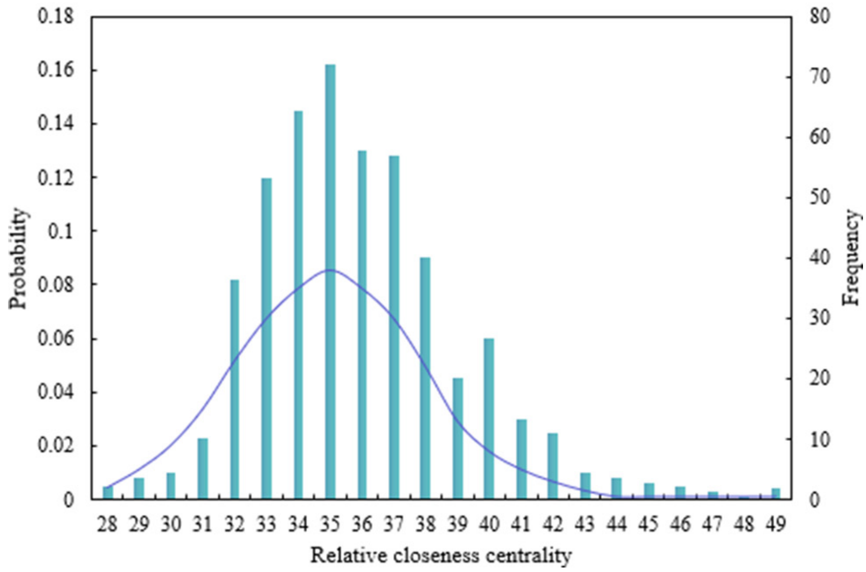

Fig. 4. Distribution of closeness centrality

Table 2. Effectiveness evaluation results

Student Number	Semester 1	Semester 2	Semester 3	Semester 4	Semester 5	Average Value	Status	Rank
1	0.857	0.758	0.846	1.302	1.748	0.837	Relative effective	9
2	0.735	0.562	0.431	0.519	0.794	0.615	Effective	2
3	0.569	0.395	0.359	0.541	0.62	0.596	Not effective	4
4	0.627	0.467	0.431	0.624	0.71	0.635	Effective	7
5	1.205	1.869	1.269	1.526	1.062	1.527	Effective	1
6	0.537	0.416	0.419	0.548	0.535	0.574	Relative effective	11
7	0.869	0.592	0.537	0.522	0.827	0.629	Effective	8
8	1.628	0.748	0.718	0.916	1.204	0.931	Not effective	5
9	0.847	0.625	0.695	0.74	0.827	0.728	Effective	10
10	1.629	1.528	1.637	1.325	1.629	1.024	Relative effective	12
11	1.527	0.451	0.412	0.461	0.927	0.619	Not effective	3
12	0.762	1.693	1.025	0.728	0.531	0.706	Effective	6
Overall	0.894	0.681	0.629	0.71	0.857	0.736	Effective	–

This paper used the software DEAP2.1 to sort out the sample data of five semesters, which were then input into the CCR model in DEA to attained the effectiveness evaluation results of students' hybrid learning interactive activities during these five semesters, then the average values were calculated and sorted out according to the size. If the value is 1, it indicates that the learning effectiveness is high; if the value is less than 1 and greater than 0.8, then it indicates that the learning effectiveness is relatively high; if the value is less than 0.8, in indicates that the learning effectiveness is low. The specific calculation results are shown in Table 2 below. According to the data in the table, students' learning effectiveness when participating in the hybrid learning interactive activities is good, the status is effective in each semester, which is consistent with the actual situations.

Table 3. Comparison and analysis of evaluation results of different evaluation methods

Student Number	DEA Evaluation	Status	Deep Learning Evaluation	Status	Changes
1	1.305	Relative effective	0.938	Effective	Increase
2	0.516	Not effective	0.624	Relative effective	Decrease
3	0.574	Relative effective	0.759	Not effective	Decrease
4	0.692	Effective	0.637	Relative effective	Increase
5	1.527	Relative effective	1.205	Relative effective	Unchanged
6	0.537	Not effective	0.571	Not effective	Increase
7	7.418	Effective	0.749	Relative effective	Unchanged
8	1.629	Relative effective	0.962	Not effective	Increase
9	0.837	Not effective	0.857	Not effective	Decrease
10	1.539	Relative effective	1.631	Relative effective	Increase
11	0.751	Not effective	0.749	Not effective	Unchanged
12	0.463	Effective	0.535	Relative effective	Decrease
Overall	0.754	Relative effective	0.716	Effective	Increase

In order to verify the effectiveness of using DEA to evaluate the effectiveness of hybrid learning interactive activities, this paper designed a comparative experiment. As can be seen from the Table 3, the evaluation result of DEA is 0.754, and the evaluation result of deep learning model is 0.716, the evaluation result of deep learning model is lower than that of the DEA.

6 Conclusion

This paper studied the effectiveness of hybrid learning activities based on learning community. At first, a theoretical model and an EIS were built for the HLCN, and its feature parameters and centrality were analyzed. Then, a HL-IAC-NR matrix was established based on learning community, and the indexes such as students' learning attention on knowledge points and their learning sentiments were attained. After that, the relative effectiveness evaluation was performed using the CCR model in DEA, and the real-time effects of different types of hybrid learning interactive activities were analyzed. In the experiments, correlation analysis was conducted on the effectiveness evaluation of hybrid learning activities, and the results showed that the input and output items of the valuation were significantly and positively correlated. Then, the distributions of the degree centrality and closeness centrality of the HLCN were given and analyzed, and the software DEAP2.1 was used to sort out the sample data of five semesters and input them into the CCR model of DEA. At last, this paper designed a comparative experiment and compared the evaluation results of different evaluation methods, and the results verified the effectiveness of using DEA to evaluate the effectiveness of the hybrid learning activities.

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