Learning Behaviors and Cognitive Participation in Online-Offline Hybrid Learning Environment

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Abstract—Hybrid learning, which integrates online teaching and offline teaching, can promote the autonomous learning ability, cooperative learning ability, and personalized development of students. Whether online learning or offline learning, the learning quality hinges on the good learning behaviors and learning participation. The existing studies have paid little attention to the learning behaviors in various dimensions. As a result, there is no scientific criterion for quantifying students' cognitive participation. This paper explores learning behaviors and cognitive participation in online-offline hybrid learning environment. Firstly, the authors provided the clustering algorithm and dimensionality reduction algorithm for learning behavior analysis under the hybrid learning environment. Then, the student cognitive participation was modeled, and the dynamic cognitive participation degree in each learning dimension was weighted through partial correlation analysis. The proposed model was proved effective through experiments.

Keywords—hybrid learning, learning behaviors, cognitive participation

1 Introduction

The rapid development of online technology and information technology has brought certain changes to the learning environment, learning contents, and learning methods in the field of education [1-6]. Hybrid learning, which is in line with the national strategy of information-based education, can promote the autonomous learning ability, cooperative learning ability, and personalized development of students [7-11]. Thanks to the quick proliferation of online learning platforms in schools at all levels, the online learning of hybrid learning is blessed with a strong technical support [12-15]. Whether online learning or offline learning, the learning quality hinges on the good learning behaviors and learning participation [16-18]. The learning quality can be enhanced by the growing participation in hybrid learning, and in return boosts that participation. The research of learning behaviors and learning participation in hybrid learning environment is of great significance to the improvement of learning level, learning effects, and personal development of students.

Zhang et al. [19] analyzed the three-year anonymous learning data of 11,392 K-12 students of a largest online extracurricular education platform in the world, revealed the online learning behaviors of the students, and deduced how the private course participation and learning results are influenced by the residence of the students, the social and economic status of their families, and the reputation/ranking of their schools. In the asynchronous forums of hybrid learning and e-learning, the learning results directly depend on the cognitive participation of learners, e.g., knowledge construction and dialog with critical thinking. Liu et al. [20] combined text mining with statistical analysis to survey learners' cognitive behaviors and the implicit contents of their posts, and manually encoded their cognitive behaviors through content analysis. Citrawathi et al. [21] explored the biological research projects of College of Mathematics and Natural Sciences, Ganesha University of Education, aiming to verify the effectiveness of problem model-based thinking on sharing learning, and to boost the student participation and learning results of in digestive system research. Their tools include questionnaires and observation forms about learning participation and responses, as well as knowledge tests on cognitive learning results. Cacciamani et al. [22] surveyed whether assigning a social tutor to each student that has registered for online college courses promotes peer participation in online discussion, the development of community awareness, and effective learning. The results show that the student participation and SC membership factor can only be improved in the presence of the social tutor. Thuku et al. [23] introduced an online course management system designed to improve course management, configure courses, add counseling issues or topics, arrange classroom demonstrations, monitor group activities, and evaluate group performance. The system allows students to register for counseling groups, determine the research problems, write papers collaboratively, upload term paper, and share the paper with classmates.

The existing studies at home and abroad are mostly shallow empirical research into learning behaviors and cognitive participation in the hybrid learning environment. Deeper research is yet to be conducted. For instance, little attention has been paid to the learning behaviors in various dimensions. As a result, there is no scientific criterion for quantifying students' cognitive participation. To solve the problem, this paper explores learning behaviors and cognitive participation in online-offline hybrid learning environment. Section 2 presents the clustering algorithm and dimensionality reduction algorithm for learning behavior analysis under the hybrid learning environment. Section 3 models the student cognitive participation, and weighs the dynamic cognitive participation degree in each learning dimension through partial correlation analysis. The proposed model was proved effective through experiments.

2 Cluster analysis

2.1 Clustering algorithm

To fully utilize the existing education resources, schools at all levels have opened online classrooms based on online learning platforms. The online classrooms integrate with offline classrooms into hybrid learning classrooms. The learning behaviors in the hybrid learning environment differ significantly from those in traditional online learning platforms.

In terms of learners, the traditional online learning platforms are open to all kinds of people, while hybrid learning platforms only accept a specific group of people: students, and offer only the courses of specific grades in specific majors. That is, the hybrid learning environment only caters to learners that are highly similar in age, location, and education background.

In terms of learning forms, the traditional online learning is featured by a low pass rate and a high dropout rate. By contrast, the online learning behaviors in the hybrid learning environment are mostly influenced by offline teaching activities, which mainly take the form of teacher-student interaction. Online learning model enriches the teacher-student interaction in offline teaching, and improves the effect of the interaction, while ensuring the dominance of teachers in teaching. In terms of performance appraisal, the hybrid learning, as integration between online and offline teaching, offers diverse ways to appraise the learning results.

Considering the novelty of learning behaviors in the hybrid learning environment, this paper chooses to analyze these behaviors through learning feature analysis, with the aid of clustering by fast search and find of density peaks (CFSFDP) algorithm. The CFSFDP is known for simple flow and good clustering effect. Let σ_i be the local density of sample point i; ξ_i be the distance from the sample point to another sample point with higher local density. Then, the flow of the CFSFDP can be detailed as follows:

Step 1. Compute the distance between sampling points, and construct a matrix.

Step 2. Compute the σ_i and ξ_i of each sampling point in the sample set.

Step 3. Multiply σ_i with ξ_i, and rank the results in descending order; based on the ranking, determine cluster heads and plot the decision map.

Step 4. Rank all sample points in descending order of local density σ_i, thereby completing the clustering.

Let $R=\{A_i\}^{M}_{i=1}$ be the sample set to be clustered; $O_r=\{1,2,...,M\}$ be the set of corresponding indices; a_i and a_j be two sample points in the sample set; $\varepsilon_{ij}=DIS(a_i, a_j)$ be the distance between sample points i and j. The sample points to be clustered are either discrete or continuous. For discrete sample points, the local density can be calculated by:

$$\sigma_{D-i}=\sum_{j}\beta\left(\varepsilon_{ij}-\varepsilon_d\right) \tag{1}$$

Where, sample points i and j are unequal but both belong to index set O_R; β can be expressed as:

$$\beta\left(a\right)=\begin{cases}1, a<0\\0, a\geq 0\end{cases} \tag{2}$$

In sample set R, the number of sample points closer than ε_d to sample point a_i can be characterized by local density. For continuous sample points, the local density can be calculated by:

$$\sigma_{C-i} = \sum_j e^{-\left(\frac{\varepsilon_{ij}}{\varepsilon_d}\right)2} \tag{3}$$

The distance ξ_i from a sample point to another sample point with a higher local density can be calculated by:

$$\xi_i = \begin{cases} \min\limits_{j \in O_R^i}\left\{\varepsilon_{ij}\right\}, O_R^i \neq \varphi \\ \max\limits_{j \in O_R}\left\{\varepsilon_{ij}\right\}, O_R^i = \varphi \end{cases} \tag{4}$$

The index se O_R can be expressed as:

$$O_R^i = \left\{l \in O_R : \sigma_l > \sigma_i\right\} \tag{5}$$

Formula (5) shows that, when sample point a_i has the greatest σ_i, it is the density peak point, and index set O_R is empty. In this case, the maximum distance from a_i to another sample point with a greater local density can be characterized by ξ_i. For a non-density peak point, ξ_i merely represents the minimum distance from a_i to another sample point.

Through the above operation, a 2-tuple (σ_i, ξ_i) can be obtained for each sample point. Then, the sample points with relatively large σ_i and ξ_i are determined as cluster heads. Observations show that the candidate cluster heads are too similar to be easily differentiated. To solve the problem, a quantitative analysis method was adopted to automatically determine the cluster heads through overall consideration of σ_i and ξ_i:

$$\chi_i = \sigma_i \times \xi_i, i \in O_R \tag{6}$$

Where, χ_i is a quantification value positively correlated to the probability that the corresponding sample point being selected as a cluster head. The cluster heads can be obtained by sorting χ_i in descending order.

2.2 Dimensionality reduction

The learning behavior sample set in the hybrid learning environment has multiple dimensions. Direct clustering of the high-dimensional sample set may cause the curse of dimensionality. Thus, it is necessary to reduce the dimensionality of the data before CFSFDP clustering. During the handling of high-dimensional learning behavior data, two problems might arise from the noises: the distances from a sample point to cluster heads are unevenly distributed, and the distance relationship in the high-dimensional space cannot be fully characterized by the low-dimensional space. To overcome these problems, this paper adopts the t-distributed stochastic neighbor embedding (t-SNE) to reduce the dimensionality. The noise disturbance was solved by the t-distribution, which effectively improves the tolerance of low-dimensional space for far sample points.

Let A and B be high-dimensional data and low-dimensional data, respectively. After adopting t-SNE, the low-dimensional probability of the Euclidean distance between sample points of learning behaviors can be expressed as:

$$w_{ij}=\frac{\left(1+\left\|b_i-b_j\right\|^2\right)^{-1}}{\sum_{l\neq k}\left(1+\left\|b_l-b_k\right\|^2\right)^{-1}} \tag{7}$$

To improve the similarity between t-distribution and Gaussian distribution, the gap between the two was described by Kullback–Leibler (KL) divergence, such that the distribution matrix of B approximates that of A. Specifically, gradient descent was selected to minimize the following loss function:

$$D=\theta_{KL}\left(T\|W\right)=\sum_f\sum_j t_j\Big|_i log\frac{t_j|_i}{w_j|_i} \tag{8}$$

The smaller the D, the higher the consistency between t-distribution and Gaussian distribution. Then, B was iteratively solved through gradient descent. The gradient can be calculated by:

$$\frac{\delta D}{\delta b_i}=4\sum_j\left(t_{ij}-w_{ij}\right)\left(b_i-b_j\right)\left(1+\left\|b_i-b_j\right\|^2\right)^{-1} \tag{9}$$

The iterative solving process was repeated until the distributions of A and B become consistent. Then, the sample data were dimensionally reduced. The t-SNE was combined with the CFSFDP to obtain the ideal cluster results of learning behaviors.

3 Cognitive participation analysis

Considering the features of online-offline hybrid learning, and relevant theories and results of learning behavior inputs and cognitive participation, this paper puts forward a theoretical evaluation model for learning behaviors and cognitive participation. As shown in Figure 1, the model covers such two dimensions as behavioral input and cognitive input, which respectively come from interactive input and emotional input.

The model outputs the overall cognitive participation of students. It can be seen from Figure 1 that cognitive participation is the joint results of the inputs of online-offline hybrid learning activities, namely, learning behaviors, teaching interaction, learning emotion, and learning cognition.

The cluster analysis results on learning behaviors merely quantify student performance in each dimension of online and offline learning, failing to reflect the overall cognitive participation of students throughout hybrid learning process. The cognitive participation of students needs to be further investigated based on the statistically collected sample set. In other words, it is necessary to determine the proportion of cognitive participation in each dimension of online-offline learning, i.e., the weight of cognitive participation in each dimension. Besides, the overall cognitive participation of students throughout hybrid learning process should be evaluated based on their cognitive participation in each learning dimension and the corresponding weight. Figure 2 shows the evaluation model for cognitive participation, which indicates that the cognitive participation of students in hybrid learning process can be evaluated from four aspects: learning content interaction, student-student interaction, teacher-student interaction, and teaching activity interaction.

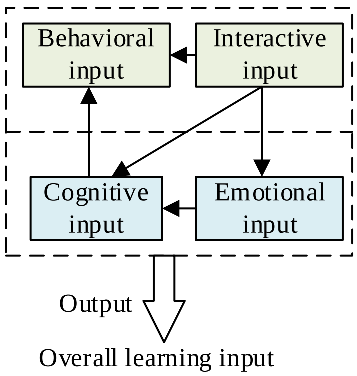

Fig. 1. Theoretical evaluation model for learning behaviors and cognitive participation

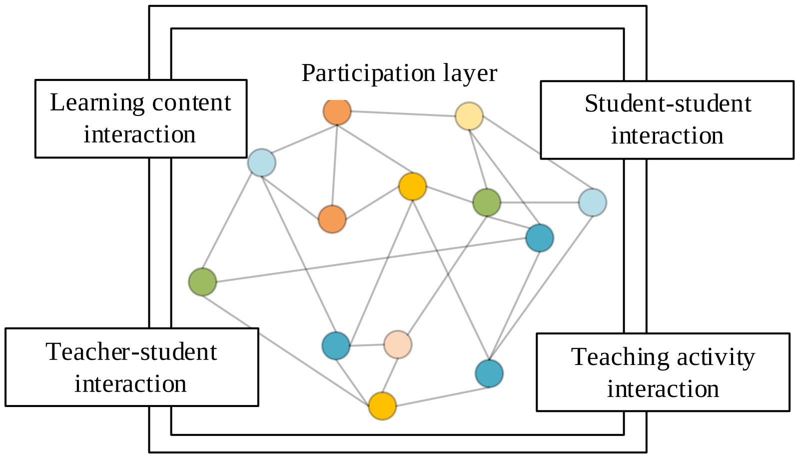

Fig. 2. Evaluation model for cognitive participation

In online-offline hybrid teaching activities, different subjects execute different tasks. Each teaching activity has a goal. The subjects will interact and communicate with each other to fulfil the common goal. The different series of operations provide teaching support to each learning dimension. The evaluation of online-offline teaching effect is the direct need of completing behavior input and cognitive participation. Figure 3 shows the conceptual model for learning behaviors and cognitive participation.

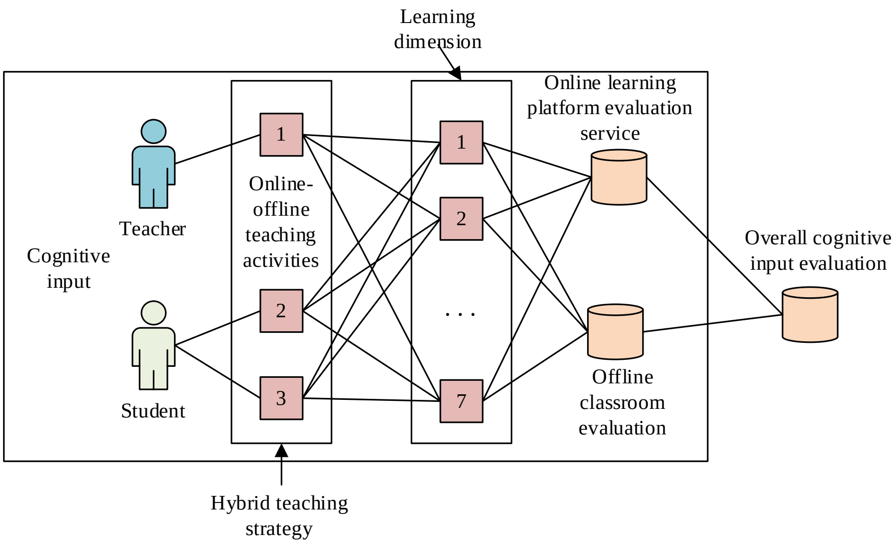

Fig. 3. Conceptual model for learning behaviors and cognitive participation

Throughout the hybrid learning process, the cognitive participation changes dynamically, due to the interplay between low-level and high-level cognition participations. To prevent the results from being distorted by subjective and other factors, this paper adopts partial correlation analysis to weigh the cognitive participation in each learning dimension. The specific steps are as follows:

Step 1. Determine the expert score matrix against a unified scoring criterion. Let $D_{ij}(i=1,2,...l)$ be the cognitive participation $Y_j(j=1,2,...7)$ in each dimension of online-offline learning evaluated by l experts. Then, the expert score matrix D can be established as:

$$D=\begin{bmatrix} d_{11} & d_{12} & d_{13} & d_{14} & d_{15} & d_{16} & d_{17} \\ d_{21} & d_{22} & d_{23} & d_{24} & d_{25} & d_{26} & d_{27} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ d_{71} & d_{72} & d_{73} & d_{74} & d_{75} & d_{76} & d_{77} \end{bmatrix} \tag{10}$$

Step 2. Use simple correlation coefficients to characterize the simple correlations between the cognitive participations of different learning dimensions. Let

$A=\{a_1,a_2,...,a_l\}$ and $b=\{b_1,b_2,...,b_l\}$ be the expert score sets of the cognitive participations in the two dimensions, respectively; λ_{ab} be the correlation coefficient between the two cognitive participations a and b; l be the number of experts. The simple correlation coefficient can be calculated by:

$$\lambda_{ab}=\frac{\sum_{i=1}^{l}a_ib_i-\frac{1}{l}\sum_{i=1}^{l}a_i\sum_{i=1}^{l}b_i}{\sqrt{\sum_{i=1}^{l}a_i^2-\frac{1}{l}\left(\sum_{i=1}^{l}a_i\right)^2}\sqrt{\sum_{i=1}^{l}b_i^2-\frac{1}{l}\left(\sum_{i=1}^{l}b_i\right)^2}} \tag{11}$$

Formula (11) shows that the simple correlation coefficient λ_{ab} falls in [-1, 1]. If $\lambda_{ab}>0$, the cognitive participations of the two learning dimensions are positively correlated; if $\lambda_{ab}<0$, the cognitive participations of the two learning dimensions are negatively correlated.

Step 3. During the hybrid learning with multiple dimensions, the cognitive participations of any two learning dimensions should be determined by controlling the influence of the cognitive participations in other learning dimensions through partial correlation analysis. Let $\lambda_{ba.a1,a2...am}$ be the partial correlation coefficients between cognitive participations a and b under the influence of the cognitive participations $a_1,a_2,...,a_m$ in other learning dimensions. Then, the N-order partial correlation coefficient can be calculated by:

$$\lambda_{ba\cdot a_1a_2...a_m}=\frac{\lambda_{ba\cdot a_1a_2...a_m}-\lambda_{ba_m\cdot a_1a_2...a_{m-1}}\lambda_{aa_m\cdot a_1a_2...a_{m-1}}}{\sqrt{1-\lambda^2_{ba_m\cdot a_1a_2...a_{m-1}}}\sqrt{1-\lambda^2_{aa_m\cdot a_1a_2...a_{m-1}}}} \tag{12}$$

The cognitive participations in the highest and lowest dimensions can be directly obtained by formulas, for they are not affected by the other dimensions. Without considering the intern period in the second semester of Grade 4, there are five mutually influencing learning dimensions of a four-year undergraduate program yet to be analyzed: second semester of Grade 1, first semester of Grade 2, second semester of Grade 2, first semester of Grade 3, and second semester of Grade 4. Thus, it is necessary to compute the partial correlation coefficients of five orders. Let $\lambda_{ba,a1}$ be the partial correlation coefficient between a and b under the influence of dimension a_1. Then, the first-, second-, third-, fourth-, and fifth- order partial correlation coefficients can be respectively calculated by:

$$\tau_{ab}=\lambda_{ba\cdot a_1}=\frac{\lambda_{ba}-\lambda_{ba_1}\lambda_{aa_1}}{\sqrt{1-\lambda^2_{ba_1}}\sqrt{1-\lambda^2_{aa_1}}} \tag{13}$$

$$\tau_{ab}=\lambda_{ba\cdot a_1a_2}=\frac{\lambda_{ba\cdot a_1}-\lambda_{ba_2\cdot a_1}\lambda_{aa_2\cdot a_1}}{\sqrt{1-\lambda^2_{ba_2\cdot a_1}}\sqrt{1-\lambda^2_{aa_2\cdot a_1}}} \tag{14}$$

$$\tau_{ab}=\lambda_{ba\cdot a_1a_2a_3}=\frac{\lambda_{ba\cdot a_1a_2}-\lambda_{ba_3\cdot a_1a_2}\lambda_{aa_3\cdot a_1a3_2}}{\sqrt{1-\lambda^2_{ba_3\cdot a_1a_2}}\sqrt{1-\lambda^2_{aa_3\cdot a_1a_2}}} \tag{15}$$

$$\tau_{ab}=\lambda_{ba\cdot a_1a_2a_3a_4}=\frac{\lambda_{ba\cdot a_1a_2a_3}-\lambda_{ba_4\cdot a_1a_2a_3}\lambda_{aa_4\cdot a_1a_2a_3}}{\sqrt{1-\lambda^2_{ba_3\cdot a_1a_2a_3}}\sqrt{1-\lambda^2_{aa_3\cdot a_1a_2a_3}}} \tag{16}$$

$$\tau_{ab}=\lambda_{ba\cdot a_1a_2a_3a_4a_5}=\frac{\lambda_{ba\cdot a_1a_2a_3a_4}-\lambda_{ba_4\cdot a_1a_2a_3a_4}\lambda_{aa_4\cdot a_1a_2a_3a_4}}{\sqrt{1-\lambda^2_{ba_3\cdot a_1a_2a_3a_4}}\sqrt{1-\lambda^2_{aa_3\cdot a_1a_2a_3a_4}}} \tag{17}$$

Step 4. After computing all partial correlation coefficients, the partial correlation coefficient matrix E can be generated by:

$$E=\begin{bmatrix}\tau_{11} & \tau_{12} & \tau_{13} & \tau_{14} & \tau_{15} & \sigma_{16} & \sigma_{17}\\ \tau_{21} & \tau_{22} & \tau_{23} & \tau_{24} & \tau_{25} & \sigma_{26} & \sigma_{27}\\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots\\ \tau_{71} & \tau_{72} & \tau_{73} & \tau_{74} & \tau_{75} & \tau_{76} & \sigma_{77}\end{bmatrix}$$
$$\omega_i=E_i\Big/\sum_{i=1}^{7}E_i,\ E_i=\sum_{j=1}^{7}\tau_{ij} \tag{18}$$

By formula (18), it is possible to weigh each dimension of online-offline learning. Note that the proportion of cognitive participation Y_i in all dimensions can be described as ω_i. The weight vector $\omega=(\omega_1,\ \omega_2,\omega_3,\omega_4,\omega_5,\omega_6,\omega_7)$ can be obtained by solving the weight ω_i of each dimension in turn.

4 Experiments and results analysis

Figure 4 shows the decision map plotted based on the planar distribution of 2-tuple (σ_i, ξ_i). There are 30 data points representing density ranking, which fall into four classes (yellow, blue, black, and red). It can be observed that data points 24 and 5 had the highest densities, and were thus determined as cluster heads. Meanwhile, the yellow data points 1, 2, and 3 were deemed as noises and removed, due to their high σ_i and ξ_i values.

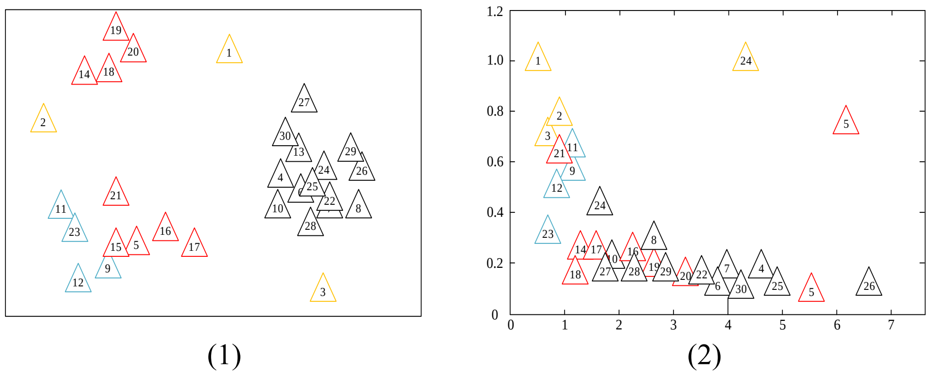

Fig. 4. 2-tuple distribution and decision map

Before analyzing cognitive participation, this paper firstly carries out a descriptive statistical analysis on the evaluation factors, including learning content interaction, student-student interaction, teacher-student interaction, and teaching activity interaction. The statistical results in Table 1 show that the mean of all four factors was greater than 3, suggesting the importance of all four factors in the samples of cognitive participation. Moreover, the standard deviation of the four factors fell in 1.02-1.52, a sign of the large difference in the response of students in different learning dimensions to different factors. Table 2 lists the correlation analysis results on each factor.

Table 1. Descriptive statistics of different evaluation factors

	Learning content interaction	**Student-student interaction**	**Teacher-student interaction**	**Teaching activity interaction**
Sample number	207	205	203	201
Minimum	1.01	1.05	1.11	1.12
Maximum	5.01	5.03	5.02	5.13
Mean	3.25	3.16	3.26	3.52
Standard deviation	1.02	1.21	1.32	1.52
Skewness	-1.12	-1.28	-1.13	-1.21
Kurtosis	1.42	1.52	1.32	1.26

Table 2. Correlation analysis results on each factor

	Learning content interaction	**Student-student interaction**	**Teacher-student interaction**	**Teaching activity interaction**
Learning content interaction	1			
Student-student interaction	0.915	1		
Teacher-student interaction	0.945	0.658	1	
Teaching activity interaction	0.885	0.862	0.852	1

The correlation coefficient between student-student interaction and learning content interaction was 0.915 at the significance level of 99%, indicating the strong positive correlation between the two. Similarly, the correlation coefficient between teacher-student interaction and learning content interaction was as high as 0.945, passing the significance test at 1% level. This means these two factors are positively correlated. In addition, the correlation coefficient of teaching activity interaction with any of the other three factors was above 0.85 at the significance level of 99%. Hence, teaching activity interaction has a strong positive correlation with learning content interaction, student-student interaction, and teacher-student interaction.

To weight the cognitive participation in each learning dimension, this paper invites 10 experts in relevant fields to rate the cognitive participations of different dimensions. The evaluation results are recorded in Table 3. The weight in each learning dimension was computed by the proposed partial correlation analysis.

The weights of the seven learning dimensions were 0.121, 0.120, 0.189, 0.177, 0.153, 0.10, and 0.12, respectively. That is, ω=(ω_1,ω_2,ω_3,ω_4,ω_5,ω_6,ω_7)=(0.121,0.120,0.189,0.177,0.153,0.10,0.12).

Finally, this paper compares and discusses the cognitive participations corresponding to different level of learning effect. Figure 5 shows the radar map of the statistics on the indices of learning effect.

Table 3. Evaluation results on cognitive participation

Expert number	**1**	**2**	**3**	**4**	**5**
Dimension 1	4.6	5.1	4.2	3.6	4.3
Dimension 2	4.2	5.1	3.8	4.5	3.2
Dimension 3	4.6	5.1	5.3	4.5	6.2
Dimension 4	3.2	4.6	5.2	6.1	4.7
Dimension 5	3.8	4.5	5.1	3.8	6.1
Dimension 6	5.3	4.5	5.1	5.3	6.2
Dimension 7	5.2	6.1	4.6	5.2	4.8
Expert number	**6**	**7**	**8**	**9**	**10**
Dimension 1	5.2	4.7	5.4	6.1	5.7
Dimension 2	5.4	6.1	6.2	5.2	6.4
Dimension 3	4.1	6.2	6.7	4.8	5.9
Dimension 4	3.6	4.8	3.9	4.3	5.2
Dimension 5	5.1	5.3	3.8	4.5	4.2
Dimension 6	4.6	5.2	5.3	4.5	4.6
Dimension 7	4.5	5.1	5.2	6.1	3.2

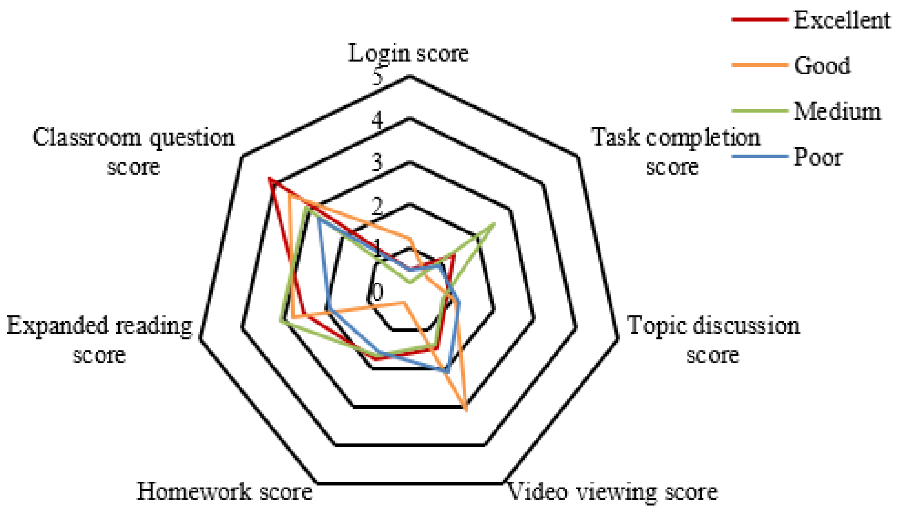

Fig. 5. Mean cognitive participation of each level of learning effect

The cognitive participations of students on the excellent, good, medium, and poor levels of learning effect can be understood through the above analysis. On this basis, several countermeasures were presented for students on each level: For those on the excellent level, teaching measures should be taken to encourage the students to maintain a good state of hybrid learning; For those on the good and medium level, the teachers should supervise and urge the students to actively participate in hybrid learning activities, especially knowledge expansion activities, aiming to enhance the overall level of cognitive participation; For those on the poor level, punitive measures could be adopted to increase students' participation in hybrid learning.

5 Conclusions

This paper explores learning behaviors and cognitive participation in online-offline hybrid learning environment. Firstly, the clustering algorithm and dimensionality reduction algorithm were expounded for learning behavior analysis under the hybrid learning environment. Next, the learning behaviors and cognitive participation were modeled, and the dynamic cognitive participation degree in each learning dimension was weighted through partial correlation analysis. After that, experiments were carried out to obtain the 2-tuple distribution and decision map, and analyze the correlations between different evaluation factors. The results show that teaching activity interaction has a strong positive correlation with learning content interaction, student-student interaction, and teacher-student interaction. Further, the evaluation results on cognitive participation were obtained, the mean cognitive participations of different learning effect levels were compared, and relevant teaching suggestions were summarized based on the experimental results.

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