Clustering Analysis of the Evaluation Data on Students' Learning under a Blended Environment

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Abstract—This paper explores the establishment of the effectiveness evaluation index system for students' learning under a blended learning environment, so as to provide some theoretical reference and guidance for the evaluation of the effect of students' learning in blended environment. In current studies, there are few quantitative analyses on the application cases or teaching practice, and there is also a lack of evaluation studies on the students as the main body of the learning process. Therefore, this paper carries out a study on the clustering analysis of the evaluation data on students' learning in a blended environment, displaying the learning effect satisfaction model for students under blended learning environment, and providing the idea of constructing a learning effect evaluation model accordingly. This paper characterizes the learning effect of students at each stage in the form of sets and formulates an evaluation index system. The analytic hierarchy process-grey clustering evaluation of students' learning effect in blended environment is carried out. On the basis of analytic hierarchy process, the evaluation index weight is determined and the evaluation grade is fixed based on the grey clustering analysis. The experimental results verify the effectiveness of the evaluation model.

Keywords—blended learning environment, evaluation of students' learning effect, evaluation index system, clustering analysis

1 Introduction

In recent years, with the continuous development of Internet technology and educational information technology, the traditional classroom is gradually replaced by blended learning ways which have been widely used. The hybrid learning environment, which combines the advantages of traditional learning methods with that of networked online learning, enables students to obtain learning resources and teachers' help equally anytime and anywhere, thus arousing their initiative, enthusiasm and creativity in learning [1–9]. As a product of the information age, networked online learning can capture the needs of students to improve their learning ability in real time, and always pays attention to the phased learning effect of students and the feedback of platform use experience, so as to provide better services for students [10–19]. Therefore, this paper takes students as the main body of the learning process, and students' satisfaction as the center to evaluate the learning quality under the blended learning environment, and explores to establish the evaluation index system for the effectiveness of the blended learning environment, so as to provide certain theoretical reference and guidance for the evaluation of the learning effect of students in blended learning environment.

Student feedback improves the quality of the teaching process. It is easier to understand if the feedback is summarized. Shidaganti et al. [20] collected feedback from students and teachers as well as performance data of students, and analyzed them using emotion analysis method. The feedback is summarized into various categories, and then the obtained data is analyzed to get a rating of students' understanding. At the same time, considering all students in the class and based on all topics, a rating of topic difficulty is obtained. Masala et al. [21] proposes an automatic feedback abstractor, which is based on the streamline integrating the most advanced natural language processing technology to extract the main views expressed by all students on each component of each course. The methods include using Bert language model to extract keywords for each course, identifying relevant contexts for repeated keywords, and clustering similar contexts. Using iClicker in the classroom allows students to get instant feedback when solving sample problems in a low-risk environment. Schuh [22] proposes that the impact of using iClickers is measured according to the average scores of students in tests, midterm exams and final exams and the final course scores before additional credit allocation. These results were compared with the average scores evaluated for the previous semesters taught by the authors without using iClicker. The progress of educational technology research and the popularity of computers have provided many tools and opportunities for teacher and other education providers to support students and teachers. Bardach et al. [23] explored whether the effectiveness of the intervention depends on the opportunity of the feedback and reflection scenarios of experts and teachers incorporated into automation. Students and teachers were randomly assigned to one of the three experimental conditions: the control group (learning activities based on online scenarios), the intervention group 1 (learning activities and feedback based on online scenarios) and the intervention group 2 (learning, feedback and reflection based on online scenarios). Grönberg et al. [24] analyzed student feedback data collected from software engineering degree courses, and then analyzed the feedback collected from all courses organized by universities. The analysis of open feedback in the experiment shows that in some software engineering course modules, the workload is heavy, while in some programming courses, the automatic code grader can be improved.

Based on the existing research results and as for the research on blended learning, domestic scholars pay more attention to the complementary advantages of traditional learning and network-based learning, the play of the leading role of teachers in guiding and monitoring the teaching process, and most of them conduct analysis from the qualitative perspective, while there is less quantitative analysis of application cases or teaching practice. The participants of blended learning and teaching are students and teachers, and the ultimate goal is to enhance students' learning ability. Students' feedback and evaluation on the effectiveness of the blended learning environment plays an important role in the rationality of teaching program of the blended learning and teaching. The existing research is also lack of evaluation research with students as the main body of the learning process. Therefore, this paper studies the clustering analysis of students' learning evaluation data in mixed learning environment. Chapter 2 displays the learning effect satisfaction model for students under blended learning environment, and provides an idea of constructing a learning effect evaluation model for students under blended learning environment. This chapter also characterizes the learning effect of students at each stage under the blended learning environment in the form of set so and formulates evaluation index system. The analytic hierarchy process-grey clustering evaluation of students' learning effect in blended environment is carried out in Chapter 3. On the basis of analytic hierarchy process, the evaluation index weight is determined and the evaluation grade is fixed based on the grey clustering analysis. The experimental results verify the effectiveness of the evaluation model.

2 Construction of evaluation system for students' learning effect under blended environment

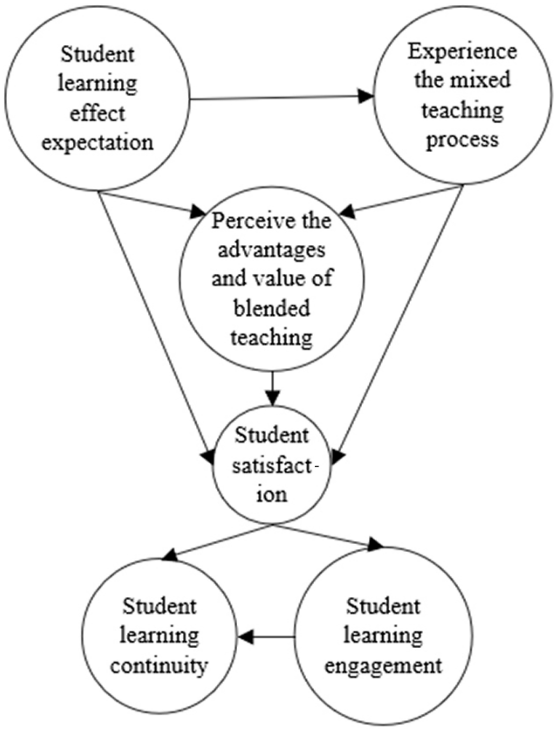


Fig. 1. Satisfaction model of students' learning effect in blended environment

Figure 1 shows the satisfaction model of students' learning effect in blended environment. Perceiving the advantages and values of mixed teaching is a subjective evaluation of the overall quality of the blended learning environment based on the actual feelings of students after they have experienced the mixed teaching process. Perceiving the advantages and values of mixed teaching directly affects the satisfaction degree of students' learning results. In this model, the satisfaction degree of students' learning effect is the outcome variable of students' learning effect expectation, experience of mixed teaching process and perception of the advantages and values of mixed teaching, and the cause variable of students' learning duration and engagement. Each variable in the model is closely related to the satisfaction degree of students' learning effect.

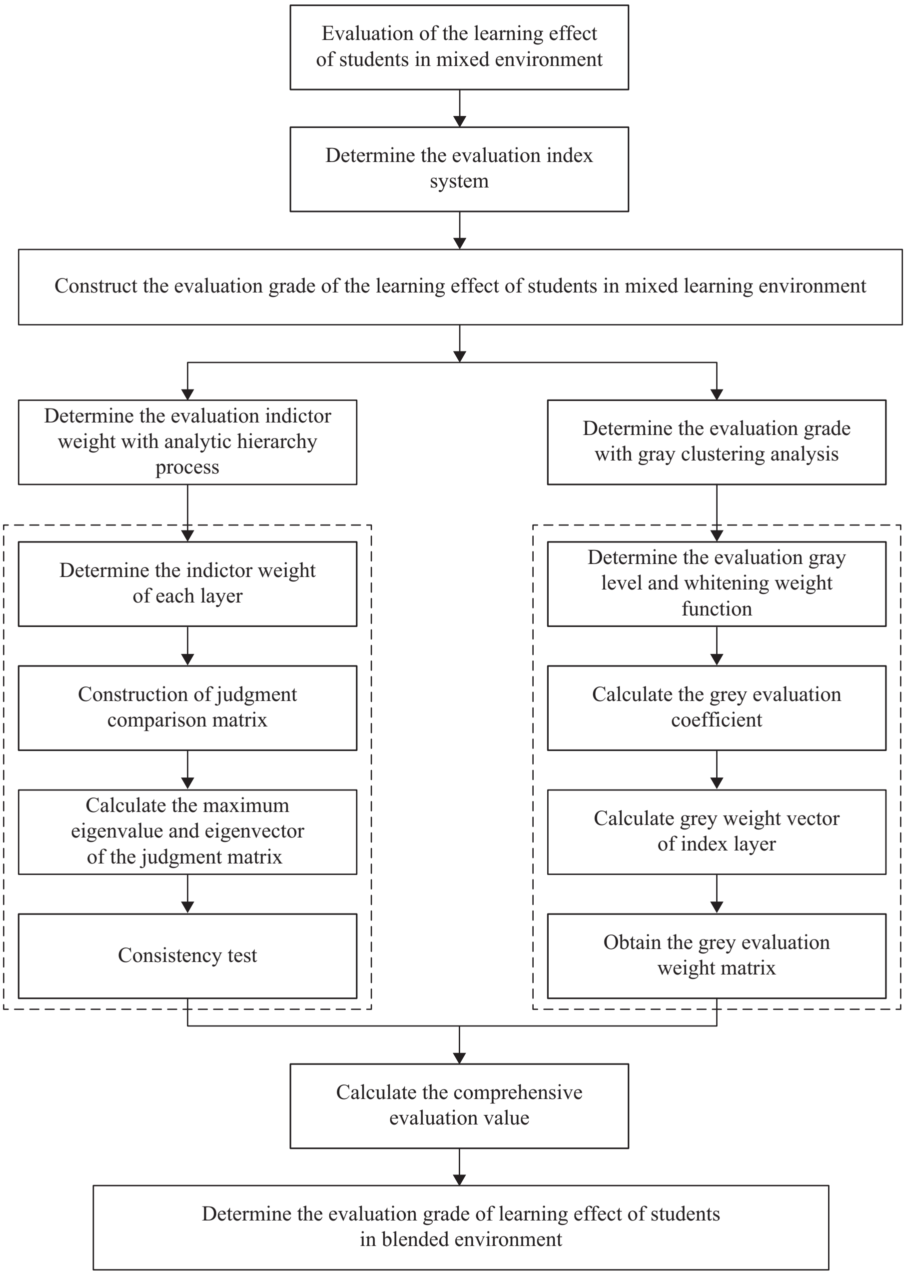


Fig. 2. Idea of constructing evaluation model for students' learning effect in blended learning environment

To reasonably and effectively evaluate the effect of students' learning effect in blended learning environment, it is first necessary to invite educational scholars with high teaching ability and rich teaching experience in the field of education to make professional judgments, screen and optimize evaluation indicators and build corresponding evaluation index system to ensure the scientificity and intensity of evaluation. For the constructed evaluation index system, this paper first weighs the indexes based on the analytic hierarchy process. The mixed learning effect grade of each stage can be calculated based on the gray clustering evaluation. The final evaluation grade of the learning effect of students under blended environment can be obtained by comprehensively processing the evaluation values of each stage. Figure 2 shows the idea of constructing the evaluation model of students' learning effect in blended learning environment.

Before constructing the evaluation index set of blended learning effect, it is necessary to identify and analyze the mixed learning effect of students. In this paper, the mixed learning effect of students at each stage will be characterized in the form of sets, which are shown as follows:

D = {teacher quality D_1, teaching process D_2, teaching resources D_3, course effect D_4, mixed learning mode D_5};

D_1 = {professional teaching ability D_{11}, online teaching ability D_{12}, mixed teaching level D_{13}, teaching attitude D_{14}, teacher ethics D_{15}};

D_2 = {process interaction and communication D_{21}, teaching content determination D_{22}, teaching time management D_{23}, teaching link design D_{24}, classroom atmosphere D_{25}};

D_3 = {online resource selection and usage D_{31}, offline resource selection and use D_{32}, resource abundance D_{33}, resource matching D_{34}};

D_4 = {teaching goal achievement D_{41}, student satisfaction D_{42}, ability improvement effect D_{43}, student learning achievement D_{44}};

D_5 = {skill driven mode D_{51}, attitude driven mode D_{52}, ability driven mode D_{53}, Barnum and Paarmann mode D_{54}}

In this paper, the evaluation criteria of students' learning effect in blended environment are divided into five levels: low mixed learning effect, relatively low mixed learning effect, medium mixed learning effect, relatively high mixed learning effect and high mixed learning effect. The corresponding values of different levels are 1, 2, 3, 4 and 5. The mixed learning effect between two evaluation levels is assigned as 0.5, 1.5, 2.5, 3.5 and 4.5. Educators with high teaching ability and rich teaching experience in the field of education are invited to score the 18 secondary mixed learning effect evaluation indexes in the evaluation index system according to the actual environment of mixed teaching and their previous blended teaching management experience. Assuming that there are l experts participating in the scoring, let o_{ijl} $(1 \le i \le 5, 1 \le j \le 6)$ be the score of each expert on each indicator, and the following scoring matrix of mixed learning effect indicators can be constructed:

$$O = \begin{bmatrix} o_{111} & o_{121} & \cdots & o_{441} \\ o_{112} & o_{122} & \cdots & o_{442} \\ \vdots & \vdots & \ddots & \vdots \\ o_{11l} & o_{11l} & \cdots & o_{44l} \end{bmatrix} \quad (1)$$

3 Analytic hierarchy process-grey clustering evaluation on the learning effect of students under mixed learning environment

3.1 Determine the weight of evaluation indicators

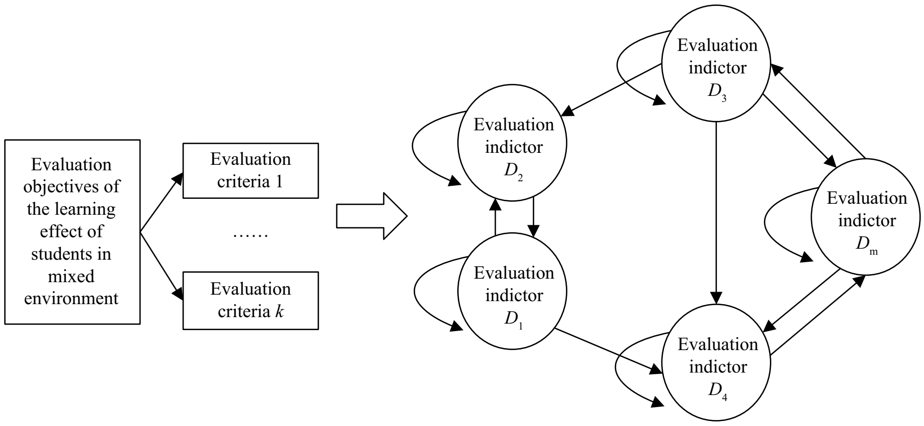


Fig. 3. Structure of analytic hierarchy process

According to the evaluation index system of the learning effect of students under blended environment, a judgment matrix is constructed for the evaluation index of mixed learning effect of different levels. The following formula provides the judgment matrix of the first level index layer:

$$D=\begin{bmatrix} d_{11} & d_{12} & d_{13} & d_{14} & d_{15} \\ d_{21} & d_{22} & d_{23} & d_{24} & d_{25} \\ d_{31} & d_{32} & d_{33} & d_{34} & d_{35} \\ d_{41} & d_{42} & d_{43} & d_{44} & d_{45} \\ d_{51} & d_{52} & d_{53} & d_{54} & d_{55} \end{bmatrix} \tag{2}$$

In d_{ij} of the above formula, when $i = j$, d_{ij} is equal to 1. d_{ij} represents the judgment value of the importance degree of the evaluation index D_i when compared with D_j, and d_{ij} and d_{ji} are reciprocal to each other. The judgment matrix of the secondary index layer is:

$$\begin{aligned} D_1 &= \left[d_{1ij} \right](i=1,2,3,4,5,\ j=1,2,3,4,5) \\ D_2 &= \left[d_{2ij} \right](i=1,2,3,4,5,\ j=1,2,3,4,5) \\ D_3 &= \left[d_{3ij} \right](i=1,2,3,4,\ j=1,2,3,4) \\ D_4 &= \left[d_{4ij} \right](i=1,2,3,4,\ j=1,2,3,4) \\ D_5 &= \left[d_{5ij} \right](i=1,2,3,4,\ j=1,2,3,4) \end{aligned} \tag{3}$$

It is assumed that $d_{ij} = 1/m\Sigma^{ml=1}n_{lij}$. The expert l judges the relative importance of the i^{th} and j^{th} indexes, and the obtained importance score is represented by n_{lij}, and the number of experts is represented by m. The dispersion coefficient is used to characterize the dispersion degree of the importance score, and the corresponding calculation formula is:

$$U_i = \bar{R}_i / l_i, \bar{R}_{ii} = \sqrt{\frac{1}{m-1}\sum_{j=1}^{m}(Y_{ij} - L_i)^2} \tag{4}$$

The comparison judgment matrix of the evaluation index system can be obtained through the comparison of the relative importance of different indicators. The matrix is represented by $D=(d_{ij})_{m\times m}$. It is obvious that $d_{ij} > 0$, $d_{ij} = 1/d_{ij}$ and $d_{ii} = 1$. The element D of the comparison judgment matrix generally satisfies $d_{ij} \cdot d_{jl} \neq d_{il}$.

Figure 3 shows the structure of AHP. For the judgment matrix D, the maximum eigenvalue and its corresponding eigenvector that satisfy $DQ = \mu_{max}Q$ are figured out. The weight of element at single ordering is represented by the component Q_i of Q. $Q^* = (Q_1^*, Q_2^*, \ldots, Q_m^*)$ is obtained by $Q_i^* = m(\prod_{j=1}^{m} b_{ij})^{1/2}$, and then normalization processing is carried out to get $Q = (Q_1, Q_2, \ldots, Q_m)$ through $Q_i^* = Q_i^*/\Sigma_{i=1}^{m}Q_i$. Then, the weight coefficient of the indicators at each level of the evaluation system for students' learning effect in mixed environment are given by the following formula, and the first level indicator level is:

$$QD = (Q_1, Q_2, Q_3, Q_4, Q_5)^T \tag{5}$$

The secondary indicator layer is:

$$\begin{aligned} QD_1 &= (Q_{11}, Q_{12}, Q_{13}, Q_{14}, Q_{15})^T \\ QD_2 &= (Q_{21}, Q_{22}, Q_{23}, Q_{24}, Q_{25})^T \\ QD_3 &= (Q_{31}, Q_{32}, Q_{33}, Q_{34})^T \\ QD_4 &= (Q_{41}, Q_{42}, Q_{43}, Q_{44})^T \\ QD_5 &= (Q_{51}, Q_{52}, Q_{53}, Q_{54})^T \end{aligned} \tag{6}$$

The comprehensive weight of the secondary indicator layer of the evaluation on the effect of students' learning in mixed environment can be calculated by the following formula:

$$\begin{aligned} D_1 &= Q_1 \times QD_1 = Q_1 \times (Q_{11}, Q_{12}, Q_{13}, Q_{14}, Q_{15})^T \\ D_2 &= Q_2 \times QD_2 = Q_2 \times (Q_{21}, Q_{22}, Q_{23}, Q_{24}, Q_{25})^T \\ D_3 &= Q_3 \times QD_3 = Q_3 \times (Q_{31}, Q_{32}, Q_{33}, Q_{34})^T \\ D_4 &= Q_4 \times QD_4 = Q_4 \times (Q_{41}, Q_{42}, Q_{43}, Q_{44})^T \\ D_5 &= Q_5 \times QD_5 = Q_5 \times (Q_{51}, Q_{52}, Q_{53}, Q_{54})^T \end{aligned} \tag{7}$$

3.2 Determination of evaluation level

In order to determine the evaluation level of mixed learning effect, this paper conducts cluster analysis. In the mixed learning effect evaluation, it is assumed that the number of evaluation objects is n, the number of evaluation indicators is m, and the number of dynamic intervals of evaluation indicators for cluster analysis is e. The cluster sample value of the i^{th} evaluation object with respect to the j^{th} index is represented by C_{ij}, and expression of the matrix of the evaluation sample for the mixed learning effect is given in the following formula:

$$O = \begin{bmatrix} o_{11} & o_{12} & \dots & o_{1m} \\ o_{21} & o_{22} & \dots & o_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ o_{n1} & o_{n2} & \dots & o_{nm} \end{bmatrix} \tag{8}$$

The mixed learning effect level of the evaluation index is expressed by the dynamic interval r ($r = 1, 2, \ldots, q$). In this paper, the mixed learning effect levels are divided into low mixed learning effect, relatively low mixed learning effect, medium mixed learning effect, relatively high mixed learning effect and high mixed learning effect, which correspond to "the first dynamic interval", "the second dynamic interval", "the third dynamic interval", "the fourth dynamic interval" and "the fifth dynamic interval", that is, the serial number of the mixed learning effect level of each dynamic interval is $r = 1, 2, 3, 4, 5$.

The whitening weight function of o is defined as the weight of the dynamic interval o, which is represented by $g(o_{ij})$. The following formula presents the whitening weight function expression:

$$g(o_{ij}) = \begin{cases} 0, o \notin [o_1, o_4] \\ \dfrac{o - o_1}{o_2 - o_1}, o \in [o_1, o_4] \\ 1, o \in [o_2, o_3] \\ \dfrac{o_4 - o}{o_4 - o_3}, o \in [o_3, o_4] \end{cases} \tag{9}$$

If $g(o_{ij})$ has no turning points o_1 and o_2, then $g(o_{ij})$ is called the lower limit whitening weight function, and its expression is given in the following formula:

$$g(o_{ij}) = \begin{cases} 0, o \notin [0, o_4] \\ 1, o \in [0, o_3] \\ \dfrac{o_4 - o}{o_4 - o_3}, o \in [o_3, o_4] \end{cases} \tag{10}$$

If $g(o_{ij})$ has no turning points o_2 and o_3, then $g(o_{ij})$ is called the median limit whitening weight function, and its expression is given in the following formula:

$$g(o_{ij}) = \begin{cases} 0, o \notin [1, o_4] \\ \dfrac{o - o_1}{o_2 - o_1}, o \in [o_1, o_2] \\ \dfrac{o_4 - o}{o_4 - o_3}, o \in [o_2, o_4] \end{cases} \tag{11}$$

If $g(o_{ij})$ has no turning points o_3 and o_4, then $g(o_{ij})$ is called the upper limit whitening weight function, and its expression is given in the following formula:

$$g(o_{ij}) = \begin{cases} 0, o \notin [o_1, +\infty] \\ \dfrac{o - o_1}{o_2 - o_1}, o \in [o_1, o_2] \\ 1, o \in [o_2, +\infty] \end{cases} \tag{12}$$

In order to facilitate understanding and calculation, the whitening weight function corresponding to the evaluation object of the mixed learning effect is understood based on the linear function. The mixed learning effect level of the first dynamic interval is level 1, which is expressed as "low mixed learning effect", and the corresponding dynamic interval is $[0, 1, 2]$. The following formula presents the corresponding expression of the whitening weight function:

$$g_1(o_{ijl}) = \begin{cases} 1, o_{ijl} \notin [0,1] \\ \dfrac{o_{ijl} - 2}{-1}, o_{ijl} \in [1,2] \\ 1, o_{ijl} \in [0,2] \end{cases} \tag{13}$$

The mixed learning effect level of the second dynamic interval is level 2, which is expressed as "relatively lower mixed learning effect", and the corresponding dynamic interval is $[0, 2, 4]$. The following formula presents the corresponding expression of the whitening weight function:

$$g_2(o_{ijl}) = \begin{cases} \dfrac{o_{ijl}}{2}, o_{ijl} \in [0,2] \\ \dfrac{o_{ijl} - 4}{-2}, o_{ijl} \in [2,4] \\ 0, o_{ijl} \notin [0,4] \end{cases} \tag{14}$$

The mixed learning effect level of the third dynamic interval is level 3, which is expressed as "medium mixed learning effect", and the corresponding dynamic interval is $[0,3,6]$. The following formula presents the corresponding expression of the whitening weight function:

$$g_3(o_{ijl}) = \begin{cases} \dfrac{o_{ijl}}{3}, o_{ijl} \in [0,3] \\ \dfrac{o_{ijl}-6}{-3}, o_{ijl} \in [3,6] \\ 0, o_{ijl} \notin [0,6] \end{cases} \tag{15}$$

The mixed learning effect levels of the fourth and fifth dynamic intervals are level 4 and level 5, which are expressed as "relatively high mixed learning effect" and "high mixed learning effect". The corresponding dynamic intervals are [0,4,8] and [0,5,10]. The following formula gives the corresponding expressions of the two whitening weight functions:

$$g_4(o_{ijl}) = \begin{cases} \dfrac{o_{ijl}}{4}, o_{ijl} \in [0,4] \\ \dfrac{o_{ijl}-8}{-4}, o_{ijl} \in [4,8] \\ 0, o_{ijl} \notin [0,8] \end{cases} \tag{16}$$

$$g_5(o_{ijl}) = \begin{cases} \dfrac{o_{ijl}}{5}, o_{ijl} \in [0,5] \\ \dfrac{o_{ijl}-10}{-5}, o_{ijl} \in [5,10] \\ 0, o_{ijl} \notin [0,10] \end{cases} \tag{17}$$

It is assumed that the evaluation coefficient of the r^{th} dynamic interval level is represented by δ_{ijr} and it can be calculated by the following formula:

$$\delta_{ijr} = \sum_{l=1}^{n} g_r(o_{ijl}) \tag{18}$$

It is assumed that the sum of all dynamic intervals r of the evaluation index is represented by: δ_{ij}, which can be calculated by the following formula:

$$\delta_{ij} = \sum_{r=1}^{n} \delta_{ijs} \tag{19}$$

Assuming that the grey weight vector of the r^{th} dynamic interval of the secondary index D_{ij} is represented by S_{ijr}, it can be calculated by the following formula:

$$S_{ijr} = \frac{\delta_{ijr}}{\delta_{ij}} \tag{20}$$

The weight vector of the secondary index D_{ij} to the five dynamic intervals is represented by S_{ijr} and can be calculated by the following formula:

$$S_{ij} = \left[S_{ij1}, S_{ij2}, S_{ij3}, S_{ij4}, S_{ij5} \right] \tag{21}$$

Based on the calculation results of the above formula, the gray weight matrix S_i of the first level index $D_i(D_1 \sim D_5)$ can be obtained:

$$S_i = \begin{bmatrix} S_{i11} & S_{i12} & S_{i13} & S_{i14} & S_{i15} \\ S_{i21} & S_{i22} & S_{i23} & S_{i24} & S_{i25} \\ S_{i31} & S_{i32} & S_{i33} & S_{i34} & S_{i35} \\ S_{i41} & S_{i42} & S_{i43} & S_{i44} & S_{i45} \\ S_{i51} & S_{i52} & S_{i53} & S_{i54} & S_{i55} \end{bmatrix} \tag{22}$$

The grey comprehensive weight vector F_i of the first level index D_i can be calculated by the following formula:

$$F_i = Q_i S_i = \left[f_{i1} \quad f_{i2} \quad f_{i3} \quad f_{i4} \quad f_{i5} \right] \tag{23}$$

The expression of grey comprehensive weight matrix S is:

$$S = \begin{bmatrix} F_1 \\ F_2 \\ F_3 \\ F_4 \\ F_5 \end{bmatrix} = \begin{bmatrix} f_{11} & f_{12} & f_{13} & f_{14} & f_{15} \\ f_{21} & f_{22} & f_{23} & f_{24} & f_{25} \\ f_{31} & f_{32} & f_{33} & f_{34} & f_{35} \\ f_{41} & f_{42} & f_{43} & f_{44} & f_{45} \\ f_{51} & f_{52} & f_{53} & f_{54} & f_{55} \end{bmatrix} \tag{24}$$

The weight vectors corresponding to the learning effects of the students in the mixed learning organization stage, the mixed learning implementation stage, the mixed learning evaluation stage, and the mixed learning extension stage are respectively represented by F_i, and the weight matrix composed of the first level index weight vectors is represented by S. The comprehensive evaluation result of the mixed learning effect GP is given by the following formula:

$$D = W \bullet S = \begin{bmatrix} f_1 & f_2 & f_3 & f_4 & f_5 \end{bmatrix} \tag{25}$$

If the value corresponding to the mixed learning effect level is denoted as Y, then $y = [1\ 2\ 3\ 4\ 5]$. The comprehensive evaluation grade H of students' learning effect in blended environment is:

$$T = D \bullet Y^E \tag{26}$$

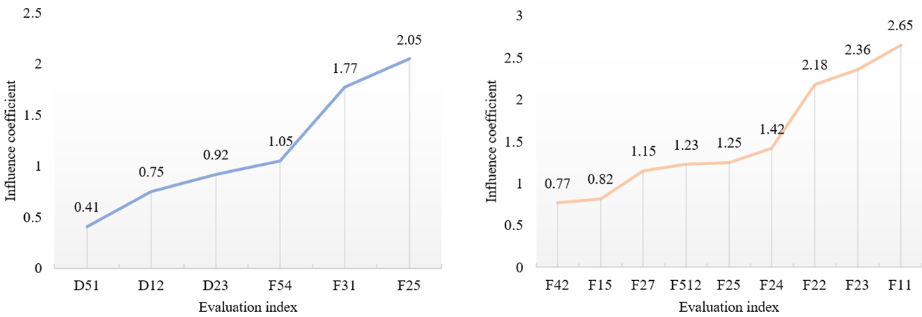
4 Experimental results and analysis

Table 1. Evaluation mean and standard deviation of different classes under different evaluation dimensions

Class Number		D_1	D_2	D_3	D_4	D_5	Grand Average
1	average value	3.52	3.16	3.94	3.17	3.25	3.18
	standard deviation	0.61	0.65	0.67	0.63	0.61	0.62
2	average value	3.96	3.48	3.25	3.51	3.96	3.43
	standard deviation	0.64	0.61	0.61	0.69	0.64	0.68
3	average value	3.57	4.26	3.57	4.57	3.11	3.42
	standard deviation	0.62	0.52	0.68	0.61	0.68	0.61
4	average value	3.19	4.74	3.52	3.48	3.13	3.27
	standard deviation	0.74	0.75	0.79	0.72	0.71	0.75
5	average value	3.58	3.27	3.62	3.81	3.29	3.08
	standard deviation	0.51	0.56	0.59	0.54	0.55	0.51
6	average value	3.27	4.03	3.24	4.39	3.17	3.09
	standard deviation	0.74	0.74	0.67	0.71	0.76	0.72

Comparison was made to tell the differences in students' learning effect under blended environment between different classes (Table 1). In the scale questions of 18 two-level mixed learning effect evaluation indicators, the average value range of the total scores of different classes in teacher's literacy D_1, teaching process D_2, teaching resources D_3, course effect D_4 and mixed learning mode D_5 is [3.08, 3.43], and the standard deviation is within the range of [0.51, 0.75], which indicates that there is no significant difference in the learning effect of students under mixed learning environment in different classes. In the evaluation of each dimension, there is the case where the average value is relatively prominent, and its basic situation is basically consistent with the average value of the total score of the scale questions of the 18 secondary mixed learning effect evaluation indicators, that is, teachers who have mixed teaching experience organize mixed teaching again can have a better teaching quality.

Figure 4 shows a detailed broken line curve drawn based on the score of impact degree of some evaluation indicators. It can be seen from the figure that in the index layer, there are 9 evaluation indexes in the scoring range of "medium mixed learning effect", including 6 evaluation indexes in the scoring range of "relatively high mixed learning effect" and 4 evaluation indexes in the scoring range of "relatively low mixed learning effect", and it is necessary to hierarchically improve and optimize the indexes in the score range of "medium mixed learning effect" and "relatively low mixed learning effect" according to the size of the influence coefficient.



(1) Relatively high blended learning effect (2) Medium blended learning effect

Fig. 4. Broken line and curve of some scores of influence coefficient evaluation indexes

Table 2. Regression analysis coefficient

	Unstandardized Coefficient		Standardized Coefficient	*t* Statistic	Significance Testing
	Value	Standard Deviation			
Constant	3.128	0.185	0.039	3.152	0.041
D_1	0.169	0.069	0.247	2.907	0.062
D_2	–0.051	0.037	–0.028	3.249	0.095
D_3	–0.169	0.015	–0.012	4.513	0.047
D_4	–0.036	0.169	–0.046	3.186	0.065
D_5	–0.041	0.158	–0.061	5.692	0.027

Table 3. Verification statistics of evaluation indicators *KMO* and *Bartlett*

Influence Factor	*KMO* Value	Degree of Freedom	Significance	Overall *KMO* Value
D_1	0.628	12	0.025	0.829
D_2	0.715	23	0.061	
D_3	0.659	4	0.095	
D_4	0.731	7	0.074	
D_5	0.795	5	0.062	

After determining the principal components of the evaluation indicators, this paper establishes a regression model to determine the evaluation value of students' learning effect under mixed environment. The independent variables of the regression model mainly include teachers' quality D_1, the teaching process $D2$, the teaching resources D_3, the course effect D_4, and the mixed learning mode D_5, and the dependent variable is the sample students' learning effect under mixed environment. The results of regression analysis are given in Table 2. It can be seen from the table that the constant of the regression equation, and the regression coefficients of D_1, D_2, D_3, D_4 and D_5 are 3.128, 0.169, −0.051, −0.169, −0.036 and −0.041 respectively. The t-statistic values are 3.152, 2.907, 3.249, 4.513, 3.186 and 5.692 respectively, and the significance test values are 0.041, 0.062, 0.095, 0.047, 0.065 and 0.027 respectively. The five values are all less than 0.05, indicating that the five independent variables of the regression equation have all passed the T inspection. After completing the T-test, *KMO* and *Bartlett* tests shall be carried out for the regression equation. Table 3 shows the statistical table based on SPSS.

As can be seen from Table 3, the validity of the five principal component evaluation indexes is good, which verifies that the construction of the evaluation index system is scientific to a certain extent.

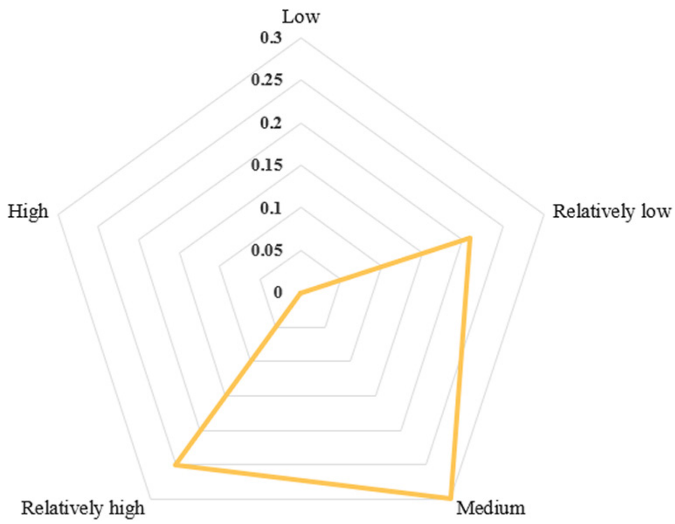


Fig. 5. Radar chart of evaluation level of students' learning effect under blended environment

The radar chart of each gray class comprehensive evaluation grade for the learning effect of students in the mixed environment obtained by calculation is shown in Figure 5. It can be seen from the figure that the overall evaluation of the learning effect of the sample students in mixed environment is in "medium" and "relatively high" status.

5 Conclusion

This paper carries out a study on the clustering analysis of the evaluation data on students' learning in blended environment, displaying the learning effect satisfaction model for students under blended learning environment, and providing the idea of constructing a learning effect evaluation model accordingly. This paper characterizes the learning effect of students at each stage in the form of sets and formulates evaluation index system. The analytic hierarchy process-grey clustering evaluation of students' learning effect in blended environment is carried out. On the basis of analytic hierarchy process, the evaluation index weight is determined and the evaluation grade is fixed based on the grey clustering analysis. The results of the experiment have statistically analyzed the average evaluation value and standard deviation of different classes under different evaluation dimensions, and verified that the basic situation of the evaluation in each dimension is basically consistent with the average value of the total scores of the scale items of the 18 secondary mixed learning effect evaluation indicators. A broken line curve is drawn based on the influence degree scores of some evaluation indexes. After optimizing the index system, a regression model is built to determine the evaluation value of the students' learning effect in mixed environment, and kmo and Bartlett tests are conducted to verify that the construction of the evaluation index system is scientific. Finally, the radar chart of the evaluation grade of the learning effect of students in mixed environment is given, which verifies that the evaluation of the learning effect of the sample students in mixed environment is in the status of "medium" and "relatively high".

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