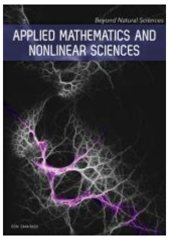
Applied Mathematics and Nonlinear Sciences, 9(1) (2024) 1-14



Applied Mathematics and Nonlinear Sciences

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A Study on the Precision Effect of Blended Learning in English Teaching and Learning

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Submission Info

Communicated by Z. Sabir
Received April 12, 2024
Accepted April 24, 2024
Available online May 3, 2024

Abstract

Realizing personalized and precise teaching using traditional English methods is challenging. This paper proposes a blended precision teaching model that relies on student portraits, using technical methods to provide tailored learning resources for every student. A deep neural network is used to extract student features, and the k-means algorithm is used to construct a clustered portrait of students. Based on the student portraits, the similarity between student objects is calculated, and the collaborative filtering method is combined to achieve personalized recommendations for English learning resources. And the learning warning model is established by considering the ranking order relationship when predicting students' English scores. Setting up the experimental class and the control class to analyze the effect of blended teaching precision, in terms of English scores, the average score of the experimental class is 6.06 points higher than that of the control class, with a significant P-value of less than 0.05, which shows a considerable difference. Its classroom teaching observation dimension score totaled 91.6, students' classroom performance and teaching effect performed well, English literacy was improved, and the mean values of each satisfaction of emotional experience showed significant differences ($P<0.05$). The mean values of several dimensions of learning motivation were higher than those of the control class, with highly significant differences in the dimensions of extrinsic goal orientation, learning beliefs, and intrinsic goal orientation ($P<0.01$).

Keywords: Blended learning; k-Means; Student portraits; Learning alert; English language teaching.
AMS 2010 codes: 97C70

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ISSN 2444-8656
https://doi.org/10.2478/amns-2024-0989

1 Introduction

With the sudden outbreak of the new crown infection epidemic, the education field of the “epidemic crisis” for “education reform opportunity” gradually turned to online and offline hybrid teaching modes [1-3]. This special period promotes the application of blended teaching mode, but as a teacher of professional courses, the transformation is not only the teaching method [4-6]. But more to think about how to make full use of online resources, platforms, and classroom environments while the teaching mode is changing, to achieve better teaching results, to change and breakthrough from the concept, so as to realize the improvement of teaching quality [7-9]. The blended teaching mode breaks through the space and time limitations of the traditional teaching mode and, at the same time, provides a richer platform and resources for English education in colleges and universities [10-11]. However, the effective combination of entry points and knowledge in the process of English education in colleges and universities is still difficult and critical.

With the continuous popularization and development of information technology, traditional English teaching methods have some limitations in responding to the needs and challenges of modern students [12-14]. The blended teaching mode provides a more flexible and diversified form of learning, integrating traditional face-to-face teaching and online teaching, bringing more flexibility and freedom to the university English classroom [15-17]. It makes English education more attractive and adaptable and better adapts to the learning needs and rhythms of different students, thus improving the attractiveness of English teaching and helping to stimulate students’ interest in learning and improve their learning effectiveness [18-20].

At the same time, with the application of blended teaching in the English classroom, English teaching is gradually moving towards the development of technology, interaction, convenience, and efficiency [21-22]. Teachers began to consider the effective strategies of English precision teaching based on the smart classroom, striving to realize the scientific integration of the smart classroom and English precision teaching and to ensure the practical development of English precision teaching with the strong support of scientific and educational means [23-25]. Therefore, the smart classroom opens up a new situation of English precision teaching, injects colorful scientific and technological elements and the atmosphere of the times, and optimizes the English teaching environment [26].

In this paper, we start with two functional modules, namely personalized recommendations of English learning resources and learning alerts, to achieve precise and personalized training for blended English teaching. The teaching function modules are all completed based on student portrait construction. Deep neural networks are used for the extraction of student features, and the k-means algorithm is used to construct accurate portraits of students by establishing optimization goals to optimize the user’s features. In the personalized recommendation of English learning resources, based on the student interest modeling and student profiles, we adopt the collaborative filtering recommendation method combined with the content and use the clustering algorithm to cluster the labels to achieve the personalized recommendation of resources. In terms of learning alerts for English learning, we combine score alerts and ranking alerts to obtain a learning alert model that integrates scores and rankings, taking into account the accuracy of score prediction for each student and the relationship between the scores of each pair of students, and reducing the judgment error of the ranking relationship.

2 A blended precision teaching model based on student profiles

2.1 Student portrait construction based on k-Means algorithm

In this paper, a deep neural network is used to perform fine-grained feature extraction from raw student features. In order to enhance the expressiveness of the extracted student features, this paper constructs positive and negative samples of the optimization objective with the key of whether there is a common learning difficulty between students and students to optimize the DNN feature extractor. Specifically, for a student, other students who have chosen the same difficulty point as the student are taken as the positive samples of the student, and students who have chosen different difficulty points are taken as the negative samples of the student, and the positive and negative samples are combined to achieve the optimization of the DNN algorithm. The detailed process of extracting features is described below.

First, the original features of student users are mapped to the hidden space in the input layer, as shown in Equation (1):

$$h_0 = W^{input} x + b^{input} \tag{1}$$

Where h_0 is the hidden features after processing by the neural network in the input layer, W^{input} is the neuron weights in the input layer, x is the original features of the student user after label encoding, and b^{input} is the bias parameters of the neurons in the input layer.

After processing the raw features by the neurons in the input layer, the user features can be further extracted and used to comprehensively portray the student's learning profile. In order to increase the nonlinear fitting ability of the DNN model and mine out the deep features of the data, this paper sets two hidden layers in the number of neural network layers and uses the relu activation function. Specifically, as in Equation (2):

$$h_l = r\left(W^l h_{l-1} + b^l\right) \tag{2}$$

Where h_l is the output of the l nd hidden layer, W^l is the parameter of the l th hidden layer neuron, b^l is the bias parameter of the l th hidden layer neuron and $r(\cdot)$ is the relu activation function.

After processing the input layer and hidden layer, the academic features of the student are further extracted. In order to obtain the final academic features of students, this paper sets an output layer to obtain the final features of users. Specifically, as shown in Equation (3):

$$h_{out} = W^{output} h_l + b^{output} \tag{3}$$

Where h_{out} is the final extracted features of student users and h_l is the output of the hidden layer.

To effectively optimize students' academic features, this paper constructs the optimization objective for similar users and uses the constructed positive and negative samples to optimize the DNN. For the constructed positive and negative samples, a classifier is used to evaluate them, as shown in Equation (4):

$$p_{ij} = sigmoid\left(f\left(\left[h_{out}^{i} ; h_{out}^{j} \right] \right) \right) \tag{4}$$

Where p_{ij} is the probability that user i and user j are common interest users, $f(\cdot)$ is the classifier, and $\left[h_{out}^{i} ; h_{out}^{j} \right]$ is the vector after the feature splicing operation for user i and user j. For the classifier, a one-layer neural network is used to obtain the output values of its spliced vectors, and a sigmoid activation function is used to calculate the probability that student i and student j are students with the same difficulty.

After obtaining the probability, the model is optimized by applying the cross-entropy loss function for binary classification, as shown in Equation (5):

$$loss = -p_{ij} \log p_{ij} - \left(1 - p_{ij}\right) \log\left(1 - p_{ij}\right) \tag{5}$$

By establishing an optimization objective to optimize user features, abstract features of student learning can be obtained so as to achieve an accurate portrait of student learning.

Considering the dimensional size of the data, in this study, the number of layers of the hidden layer of the deep neural network is set to 2 layers, the number of neurons is set to 6, and the output layer is set to one neuron.

The absolute size of the values in the table reflects the strength of the features, with negative values indicating negative feedback, i.e., Having relatively poor learning attitudes and positive values indicating positive feedback, i.e., having relatively good learning attitudes. Good habits can be developed in the same way.

2.2 Personalized Recommendation of English Learning Resources

2.2.1 Student User Model Predictions

Based on user interest modeling and student profiling, the similarity of users can be represented by user interest groups and local similarity within the group. The near neighbor users thus obtained are based on an interest group:

$$Sim\left(u_i, u_j\right) = gSim\left(u_i, u_j\right) * r + ISim\left(u_i, u_j\right)_{interest_1} * (1 - r) \tag{6}$$

Where $gSim\left(u_i, u_j\right)$ represents the overall similarity of users. r represents the weighting system $(0 < r < 1)$, while $ISim\left(u_i, u_j\right)_{interes\ t_t}$ represents the local similarity of users based on a group. $gSim\left(u_i, u_j\right)$ and $ISim\left(u_i, u_j\right)_{interes}^{t}$ can be obtained by using Pearson's formula above, only that the meaning of each parameter is different when they are calculated, which is relatively simple, and readers can understand it by themselves. Where $gSim\left(u_i, u_j\right)$ is calculated on the basis of the public same interest group, $ISim\left(u_i, u_j\right)_{interest\ 1}$ is obtained on the interest tag group based on the weights obtained by the TF-IDF method (again emphasizing that this data, not the data processed by the association rules). When calculating $ISim\left(u_i, u_j\right)_{interest}$, the more the number of common tags the more reliable the calculated similarity is due to the influence of the weights of the common tags within that interest group. So we can make some changes to $ISim(u_i,u_i)_{\text{int } cres\ r_i}$:

$$ISim(u_i,u_j)_{\text{int } eres\ t} = \frac{\min\left(\left|I_{u_i r u_j}\right|, r\right)}{r} ISim(u_i,u_j)_{\text{int } erest\ u_i} \tag{7}$$

The user's predicted interest tag group has an average rating

Find the nearest neighbor of the user by having the $gSim(u_i,u_j)$ obtained from Pearson's formula above. I.e:

$$Neighbors(u) = \{Neighbor_1, Neighbor_2, \ldots, Neighbor_n\} \tag{8}$$

Where $Neighbor_1, Neighbor_2, \ldots, Neighbor_n$ decreases sequentially according to user likelihood and the average prediction of user u for the k rd classification, the rating can be expressed as follows:

$$P(u, \text{int}\, erest_j) = \overline{\text{int}\, erest_u} + \frac{\sum_{u_k \in Neighbors(u)} gSim(u,u_k)\left(R_{u_k,\text{int}erest_i} - \overline{\text{int}\, erest_{u_k}}\right)}{\sum_{u_k \in Neighhs\sin(u)} gSim(u,u_k)} \tag{9}$$

Where $\overline{\text{int}\, erest_u}$ denotes u the average weight of each interest, and $R_{u_k,\text{int}erest_i}$ denotes the average weight of the user u_k for each of the i interest categories.

Predicting the user's predicted weights for labels:

$$P(u,i) = \begin{cases} \overline{R_{u,\text{int}erest}}^{\,i} + \dfrac{\sum_{u_j \in INeighbor(u)} Sim(u,u_j)\left(R_{u_j,i} - \overline{R_{u_j,\text{int}crest}}\right)}{\sum_{u_j \in Neighhor(u)} Sim(u,u_j)} \\ P(u, \text{int}\, erest^i) + \dfrac{\sum_{u_j \in Neighbor(u)} Sim(u,u_j)\left(R_{u_j,i} - \overline{R^i_{u_j,\text{int}eresi}}\right)}{\sum_{u_j \in Neighbor(u)} Sim(u,u_j)} \end{cases} \tag{10}$$

This formula reflects the fact that the user's predicted weight for a tag i needs to be obtained in two different ways; if the user does not have a predicted weight for the tag's interest tag group classification, the following formula is used, where $P(u, \text{int}\, erest^i)$ expresses the user's predicted weight for the tag's interest tag group, and the computation process has been explained above. Instead, the above Equation is used, and its first half expresses the average predictive weight of user u for the classification of the interest group in which the tag is located.

2.2.2 Implementation of learning resource recommendation

1) Direct content-based recommendation

Earlier, this paper predicted a more accurate user model using a hybrid approach. This model is based on a weight matrix for user tags. The TF-IDF method has enabled us to obtain a resource-tag weight matrix. Then, it is easy to generate personalized recommendations directly based on this:

$$Rat(u,item) = User\_profile(u) * \mathrm{Re}source\_profile(item) \tag{11}$$

Reduced to:

$$Rat(u,item) = \sum weight_u ser(tag_i) * weight_i tem(tag_i) \tag{12}$$

Then the recommendation is generated by the size of $Rat(u,item)$.

2) Collaborative filtering based recommendation

The set of similar users, i.e., The clustering method, first clusters the users to obtain neighboring users. The use of clustering methods here is similar to the clustering of labels in the previous chapter. Here, only the specific meanings of some variables have been changed. In this instance, the label used for clustering is the user. And in the clustering of the items or resources, there is a proxy for the label.

3) Output of personalized recommendation

In the previous section, we obtained two sets of recommendations. Although the first set of results is realized using a content-based approach, the second set of recommendations is realized using a collaborative filtering approach. However, since the user models of both approaches are predicted using a hybrid model approach, it can actually be said that both approaches generate recommendations in a hybrid mode. Finally, the recommendation data generated by the two sets of recommendations is jointly displayed to the user so that the user can receive a more accurate personalized recommendation.

2.3 Learning Early Warning Models

In the process of training the learning early warning model (SRIM), two aspects should be taken into account: one is the need to focus on the score prediction accuracy of each student to reduce the prediction error of single scores, and the other is the need to focus on the high and low score relationship between each pair of students to reduce the judgment error of the ranking order relationship. The desired learning alert model can only be obtained by considering both goals simultaneously.

X_i and X_j are the inputs to the model for student i and student j, respectively, and the order of the inputs for the two students cannot be switched in this model. X_i and X_j will be input into the score prediction part first to get the predicted course grades for both students $\hat{s}_i$ and $\hat{s}_j$. The structure and parameters of both score prediction parts must be identical; the distinction is that their outputs must be a real value, not a vector.

In order to achieve a combined prediction of scores and rankings, score prediction results $\hat{s}_i$ and $\hat{s}_j$ need to function as both absolute and relative scores.

In order for $\hat{s}_i$ and $\hat{s}_j$ to function as absolute scores for predicting a single student's course grade, in this paper, they are compared with the true scores of two students, s_i and s_j, respectively, and the squared error between the true and predicted values is calculated for each of them to obtain the value of the loss function for the score prediction task, l_{si} and l_{jj}, as shown in Equation (13) and Equation (14):

$$l_{si} = \frac{1}{2}\left(\hat{s}_i - s_i\right)^2 \tag{13}$$

$$l_{sj} = \frac{1}{2}\left(\hat{s}_j - s_j\right)^2 \tag{14}$$

In order for $\hat{s}_i$ and $\hat{s}_j$ to function as relative scores for determining the rank order relationship between two students, in this paper, they are first subtracted to obtain the difference between the predicted scores of the two students, $\hat{d}_{ij}$, i.e., Equation (15):

$$\hat{d}_{ij} = \hat{s}_i - \hat{s}_j \tag{15}$$

In the above Equation, the order in which the two predicted scores are subtracted cannot be switched arbitrarily either, and $\hat{s}_j$ must be subtracted from $\hat{s}_i$. Next, this paper uses a sigmoid function to obtain the probability $p\left(r_i > r_j\right)$ that student i 's ranking is ahead of student j 's, which is given by Equation (16):

$$p\left(r_i > r_j\right) = \frac{1}{1+e^{-\hat{d}_{ij}}} = \frac{1}{1+e^{-\left(\hat{s}_i - \hat{s}_j\right)}} \tag{16}$$

Once the output $p\left(r_i > r_j\right)$ of the ranking prediction task is calculated, it can be substituted with the label y_{ij} that indicates the true ranking order relationship to obtain the loss function l'_{rij} of the ranking prediction task in SRIM for this sample.

In the following, the above three loss functions are weighted and summed in the manner of Eq. (17) to obtain the value of each pair of students' contribution to the loss function l_{ij}:

$$l_{ij} = \left(l_{si} + l_{sj}\right) + \alpha l'_{rj} \tag{17}$$

The left and right terms in the above Equation are the loss function for the score prediction task, 1, and the loss function for the ranking prediction task, l'_{rj}. In this paper, the coefficient of the former is always set to $\left(l_{si} + l_{sj}\right)$, so that the SRIM always takes into account the score prediction effects of the two students and prevents the score prediction error from being too large; and α is the coefficient of the latter, which is a non-negative hyperparameter that represents the weight of the ranking task in the SRIM. This constructs the only loss function in this MTL model, which can be used to find the optimal parameters of the model using gradient descent.

Finally, the total loss function value L for the SRIM training set is obtained by summing over all student pairs consisting of m students in the training set as a form of Eq. (18):

$$\begin{aligned} L &= \frac{2}{m(m-1)}\sum_{\substack{i,j\\i<j}} l_{ij} \\ &= \frac{2}{m}\sum_{i=1}^{m} l_{si} + \frac{2\alpha}{m(m-1)}\sum_{\substack{i,j\\i<j}} l'_{rij} \\ &= \frac{1}{m}\sum_{i=1}^{m}\left(\hat{s}_i - s_i\right)^2 \\ &\quad + \frac{2\alpha}{m(m-1)}\sum_{\substack{i,j\\i<j}}\left[\frac{2}{1+e^{-\left|r_i - pr_i\right|}} - 1\right]\cdot Entropy\left(y_{ij}, p\left(r_i > r_j\right)\right) \end{aligned} \tag{18}$$

In Equation (18), when $\alpha = 0$, the total loss function L then degenerates into the mean squared error loss function that is often used in the training of ordinary score warning models, except that there is a difference of a factor of 2 between the two, which is caused by the fact that each of the input samples to the SRIM contains two students.

Therefore, the larger the value of α is set, the more importance the model places on the ranking prediction effect during training, and vice versa for the score prediction effect. By reasonably choosing the value of α, it is possible to improve the ranking prediction accuracy at the expense of a certain score prediction effect, so as to achieve the learning alert goal of comprehensively predicting scores and rankings, and improve the effect of learning alert.

3 Analysis of the effect of blended teaching precision

Among the English majors in a school, two classes were randomly selected as experimental and control classes, each with 50 students, for a one-semester (4-month) teaching experiment. The traditional teaching method was still in use by the control class, but the experimental class utilized the blended precision teaching method proposed in this paper.

3.1 Pre- and post-test control of English learning achievement

The subject students were organized into groups according to the score bands, with those who scored 120 points (150-point scale) or more in English as the superior group, those who scored 90 to 119 points (150-point scale) as the intermediate group, and those who scored less than 90 points (150-point scale) as the inferior group. The average scores of the experimental and control classes before and after the experiment are shown in Table 1. Before the experiment, there was not much difference between the average grades of the superior, intermediate, and poor groups of the experimental and control classes, and there was only a difference of 1.37 points between the average grades of the experimental class and the control class. After a semester-long (4 months) teaching experiment in the experimental class, the superior group of the experimental class was 7.25 points higher than the control class, showing a significant difference ($p<0.05$). The difference in the grades of the inferior group of the two classes amounted to 11.36 points, showing a highly significant difference ($P<0.01$). The average score of the experimental class was 6.06 points higher than that of the control class, and its significant P-value was less than 0.05, indicating a significant difference. This indicates that blended precision teaching had a more significant impact on both superior and poor students.

Table 1. English performance

-		Before experiment				After experiment			
		Whole class	Top student	Average student	Underachiever	Whole class	Top student	Average student	Underachiever
Experimental group	Average score	100.64	124.37	103.62	73.93	101.29	133.85	100.55	69.47
	Standard deviation	12.78	4.89	4.87	9.88	22.18	6.51	8.56	18.45
Control class	Average score	102.01	129.25	105.16	71.62	95.23	126.26	101.32	58.11
	Standard deviation	14.9	4.21	4.3	7.7	26.88	6.47	8.77	20.78
P		>0.05	>0.05	>0.05	>0.05	<0.05	<0.05	>0.05	<0.01

3.2 Comparison of classroom teaching observation and evaluation

The classroom teaching observation evaluation mainly includes four dimensions: teaching design, teaching behavior, learning process, and learning effect. Taking 50 students in the experimental class as the object of observation, based on a specific teaching case of an English teaching and explaining class, the classroom observation scale of class time was collected. The evaluation of the observation dimensions of classroom teaching observation is shown in Table 2. The statistics show that the scores of all four dimensions are relatively high, all of them around 90%. Among them, the score for teaching behavior is 95.46%. This is the fact that under the blended teaching mode, English teaching has been precise and changed for both teachers and students and has been integrated into the classroom to promote their own development. In addition, the students' participation in the learning process is high; they learn from each other and complement each other's strengths and weaknesses, and their score rate is also 91.42%. The classroom teaching observation dimension score was 91.6, and the student's classroom performance and teaching effectiveness were successful.

Table 2. Teaching observation in class

Observation dimension	Actual score	Target score	Mean deviation	Scoring average
Teaching design	21.33	24	2.66	88.88%
Teaching behavior	24.82	26	1.97	95.46%
Learning process	21.94	24	2.04	91.42%
Learning effect	23.54	26	2.14	90.54%
Total	91.63	100	8.81	91.63%

3.3 Teaching emotional experience feedback

Affective experience is a reflection of students' experience and satisfaction during the process of learning knowledge. Emotional experience mainly covers four indicators: teaching process, evaluation mode, assessment mode, and teaching effect. The emotional experience of the experimental class and the control class based on different teaching methods is shown in Figure 1, with the left side of each index representing the control class and the right side representing the experimental class. Through statistical analysis, it was found that the mean value of satisfaction of the experimental class was higher than that of the control group, and there were significant differences between the experimental class and the control class in the two dimensions of the teaching process ($T=-3.65$, $P=0.048<0.05$) and assessment mode ($T=-4.64$, $P=0.031<0.05$). There is a highly significant difference in the dimensions of assessment methods ($T=-2.73$, $P=0.006<0.01$) and teaching effectiveness ($T=-4.37$, $P=0.007<0.01$). It can be seen that the experimental class students are more satisfied with the precise teaching process, evaluation method, assessment method, and teaching effect of the blended teaching model.

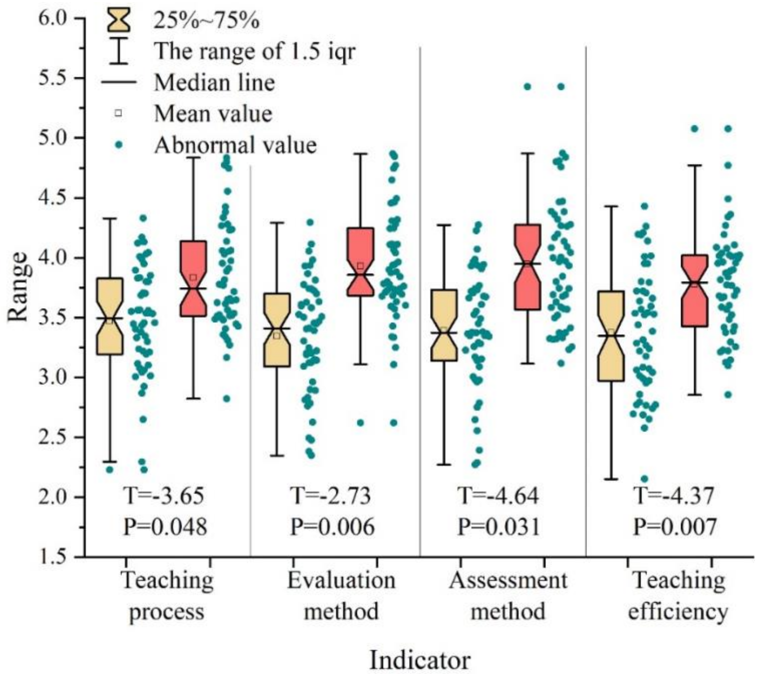

Figure 1. Emotional experience

3.4 Effectiveness of Learning Motivation Development

Motivation to learn is the driving force behind student learning, and there are different categories of division. Learning motivation is mainly divided into six dimensions: self-efficacy, extrinsic goal orientation, task value, learning beliefs, intrinsic goal orientation, and test anxiety. The different dimensions of learning motivation of the experimental and control classes after the blended precision teaching experiment are shown in Table 3. In the dimension of test anxiety, the dimension means of the experimental class and the control class were 4.58 and 4.56, respectively, with a difference of only 0.02 between the means of the two sides, which was not significant ($P>0.05$). On the other hand, in the dimensions of self-efficacy ($T=-2.637$, $P=0.021<0.05$) and task value ($T=-3.535$, $P=0.047<0.05$), there are significant differences between the experimental class and the control class, and the mean values of the dimensions of the experimental class are higher than those of the control class, which are higher than those of the control class, which are higher than those of the experimental class, which are higher than those of the control class, respectively, by 0.46 and 0.69. Outside of the goal orientation ($T=-3.26$, $P= 0.008<0.01$), learning beliefs ($T=-3.101$, $P=0.003<0.01$), and intrinsic goal orientation ($T=-4.077$, $P=0.004<0.01$) dimensions, there is a highly significant difference between the experimental and control classes. It can be seen that the blended teaching mode can more accurately stimulate students' motivation to learn and make students more motivated to learn, which is of great significance in promoting students' learning, and also, side by side indicates that the teaching effect of this teaching mode is effective.

Table 3. Learning motivation

Dimension	Class	Mean value	Standard deviation	T	P
Self-efficacy	Control class	4.82	0.865	-2.637	0.021*
	Experimental group	5.25	0.772		
The orientation of external goals	Control class	4.68	0.855	-3.26	0.008**
	Experimental group	5.15	0.79		
Task value	Control class	4.46	1.004	-3.535	0.047*
	Experimental group	5.14	0.844		
Learning belief	Control class	4.53	1.068	-3.101	0.003**
	Experimental group	5.16	0.842		
The orientation of the inner goal	Control class	4.54	0.892	-4.077	0.004**
	Experimental group	5.28	0.813		
Test anxiety	Control class	4.56	1.212	-0.013	0.681
	Experimental group	4.58	1.068		
* p<0.05 ** p<0.01					

3.5 Comprehensive Evaluation of English Literacy

Students' English literacy encompasses four indicators: language ability, thinking quality, cultural awareness, and learning ability. As shown in Table 4, there is no significant difference (P>0.05) between the experimental class and the control class in the indicators of English literacy before conducting the experiment of the blended precision teaching model, which means that the experimental class and the control class have comparable levels of English literacy before the experiment. After the experiment was conducted, there were significant differences (P<0.05) in the three dimensions of quality of thinking, cultural awareness, and learning ability, and the indicators of the experimental class were higher than those of the control class by 0.28, 0.34, and 0.35, respectively, while in the indicator of language proficiency (T=-3.18, P=0.002<0.01), a highly significant difference was shown, with the experimental class having more than the control class in the mean value of the dimension by 0.45. The blended precision mode of teaching resulted in students with higher English literacy than those in the traditional mode of teaching.

Table 4. English literacy

Indicator	Time stage	Class	Mean value	Standard deviation	T	P
Language competence	Before experiment	Control class	3.34	0.522	-1.131	0.257
		Experimental group	3.47	0.552		
	After experiment	Control class	3.25	0.703	-3.18	0.002**
		Experimental group	3.7	0.657		
Thinking quality	Before experiment	Control class	3.33	0.528	-0.706	0.48
		Experimental group	3.42	0.562		
	After experiment	Control class	3.43	0.569	-1.533	0.027*
		Experimental group	3.71	0.612		
Cultural consciousness	Before experiment	Control class	3.36	0.616	-0.265	0.791
		Experimental group	3.3	0.628		
	After experiment	Control class	3.32	0.627	-0.548	0.028*
		Experimental group	3.66	0.715		
Learning ability	Before experiment	Control class	3.52	0.541	-0.568	0.566
		Experimental group	3.54	0.599		
	After experiment	Control class	3.42	0.584	-0.808	0.013*
		Experimental group	3.77	0.642		
* p<0.05 ** p<0.01						

4 Conclusion

The purpose of this paper is to propose a blended precision teaching model that is based on student portraits and to create a personalized resource recommendation method that is based on student portraits. We analyze and explore the precision effect of English teaching by setting up an experimental class and a control class for a 4-month teaching experiment. The summary of the study is as follows:

1) In terms of English scores, there is little difference in the average scores of the superior, intermediate, and poor groups of the experimental and control classes before the experiment. After the teaching experiment, the grades of the superior group and the inferior group of the experimental class showed significant differences ($P<0.05$). The superior group of the experimental class was 7.25 points higher than the control class, showing a significant difference ($P<0.05$).

2) The scores for the four dimensions of classroom teaching observation and evaluation, namely, instructional design, teaching behavior, learning process, and learning effect, are all relatively high, around 90%. Among them, the scoring rate for teaching behavior is 95.46%, and the scoring rate for the learning process is also 91.42%. The dimension score of classroom teaching observation totaled 91.6, and the student's classroom performance and teaching effectiveness performed well.

3) The mean value of satisfaction of each index of emotional experience in the experimental class is higher than that of the control group, and there is a significant difference between the experimental class and the control class in the dimensions of the teaching process and assessment method ($P<0.05$) and a highly significant difference in the dimensions of evaluation method and teaching effect ($P<0.01$).

4) In terms of learning motivation, there are significant differences between the experimental and control classes in the dimensions of self-efficacy and task value ($P<0.05$), and the mean values of the dimensions of the experimental class are higher than those of the control class, by 0.46 and 0.69, respectively. There are highly significant differences between the experimental and control classes in the dimensions of extrinsic goal orientation, learning beliefs, and intrinsic goal orientation ($P<0.01$).

5) As far as English literacy is concerned, there is a significant difference ($P<0.05$) between the experimental class and the control class in the three dimensions of quality of thinking, cultural awareness, and learning ability after the experiment of the blended and precise teaching model, and the indicators of the experimental class are higher than those of the control class by 0.28, 0.34, and 0.35, respectively. In the language proficiency indicator, a highly significant difference was shown, with the experimental class having 0.45 more dimension means than the control class.

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