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Online and Offline Blended Teaching of Calligraphy Based on Deep Learning

Shuhang Li*

School of Economics and Management, Shenyang Institute of Technology, Shenyang, Liaoning, 113122, China

**corresponding author*

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Abstract: Affected by the COVID-19 epidemic, students' learning progress has been affected in various aspect, and blended teaching has become a new option. Although the impact of the epidemic on teaching has been greatly reduced, the effect of pure online and offline teaching is not ideal. In this context, this paper mainly proposed improvements to the current calligraphy blended teaching model through deep learning. Personalized content recommendation is made according to the actual learning situation of students' course content, so as to strengthen students' understanding and cognition of calligraphy course content. Based on the deep learning theory, this paper constructed the IUNeu calligraphy course content recommendation model, and selects the third-grade students of school A as the experimental objects to conduct an experimental comparative analysis of different teaching modes. This paper analyzed from three perspectives of calligraphy theory course teaching, calligraphy practice course teaching and calligraphy ability. The experimental results were shown as follows. In the teaching of calligraphy theory courses, the pass rates of the students in the experimental group were 26.6%, 26.7%, 13.3%, 40%, and 40% higher than those in the control group in the origin of Chinese characters, the structure of Chinese characters, the strokes of Chinese characters, the physical evolution of Chinese characters, and the stippling of Chinese characters, respectively. In terms of calligraphy ability, the calligraphy ability of the students in the experimental group was higher than that of the control group, and the proportion of students in the four calligraphy appreciation abilities of connotation, artistic conception, temperament and distinguishing strokes was 26.6%, 26.7%, 33.4% and 13.3% higher than that of the control group. This showed that the effect of the new calligraphy course teaching mode based on deep learning is remarkable, and it also provided a certain experimental basis for the follow-up calligraphy course education reform.

1. Introduction

Affected by the epidemic, the offline course teaching activities of many schools have been impacted to varying degrees. In order not to affect students' course learning, many schools have launched online teaching behaviors. Online learning platforms such as MOOC are used to carry out course teaching activities, so that students can enjoy course learning at home. But over time, it turns out that there are many problems with pure online teaching, and students' learning efficiency and learning effect deviate from the expected results. The traditional teaching mode cannot meet the current teaching environment. Whether it is online learning or offline learning, there is no departure from the old teaching thinking mode. Therefore, it is imperative to seek a new teaching mode.

This paper mainly analyzed the connection between teachers, calligraphy courses and students in the traditional online and offline teaching process, and used the advantages of deep learning to realize personalized recommendation of calligraphy course content for students. On the basis of this theory, combined with the research of others, an IUNeu model with auxiliary information is proposed. The model can follow up the learning situation of each student's calligraphy course in real time, analyze the learning situation of each student's calligraphy course, and then recommend the corresponding course content according to the analysis results. The calligraphy course teaching mode under deep learning not only breaks the traditional offline "cramming" teaching, but also absorbs the advantage that online teaching can record students' course learning information. Combining the advantages of the two, we would teach students a new calligraphy course, make up for the students' own shortcomings, strengthen the students' cognition of the course, and provide practical significance for the learning of the calligraphy course.

The online and offline teaching mode is not unfamiliar, especially in recent years, due to the impact of the epidemic, many schools have launched online and offline teaching activities and achieved certain results. Wu Y conducted research on international students' Chinese learning through online and offline teaching, and analyzed the whole teaching. The results showed that online teaching improves the interest and quality of Chinese language learning, and enhanced the international students' understanding and recognition of Chinese language and culture[1]. Taking the course "College English" as an example, Wu X discussed the relationship between blended teaching and ideological and political teaching combined with the analysis of teaching methods of blended teaching. Based on these two parts, he put forward suggestions for the reform of the evaluation system [2]. Taking college English courses as an example, Wang X constructed a blended learning model based on SPOC, and conducted an investigation and research on students' performance and autonomous learning behavior. The results showed that the blended learning model stimulates students' learning motivation and autonomous learning ability [3]. Wang Y proposed blended teaching for English teaching, which combined the advantages of online teaching and traditional face-to-face teaching to improve students' writing interest and writing ability [4]. Ige O A explored the impact of blended instructional strategies on student achievement in civic education concepts in a mountain learning ecology. He adopted the idea of pre-test-post-test, control group and quasi-experimental design to conduct relevant experimental verification on 78 students [5]. In the previous related research, most of the research content only researched the characteristics of online and offline blended teaching, and did not deeply analyze the shortcomings of blended teaching. On this basis, he proposed a deep learning method to improve the shortcomings of the current online and offline blended teaching such as insufficient information utilization. He proposed a new blended teaching model based on deep learning, and learned about the current research on deep learning in teaching. Doleck T explored the utility and applicability of deep learning for educational data mining and learning analysis using two educational datasets, which have high performance advantages over other algorithms [6]. Li Q improved and educated physical education and training training through deep learning. Experimental results showed that compared with traditional methods, the proposed method achieves extraordinary physical activity monitoring effect and can help students and improve related aspects of physical fitness [7]. Tong M proposed a deep learning-based model to classify web pages. This effectively solved the problem of feature concatenation and vector sparseness in the process of deep feature fusion in the network, which has strong efficiency and high accuracy in classification [8]. It can be seen that deep learning has great advantages for data processing generated in education, and this research provides certain ideas for the development of this paper.

On the basis of previous research, this paper conducted an in-depth analysis of the problems existing in the current online and offline blended teaching of calligraphy, and groundbreakingly proposed a deep learning theory for the current calligraphy teaching. With the help of relevant theories, the IUNeu course content recommendation model is constructed, and information is taken and processed for the problems existing in the current students' learning process of calligraphy courses. Then, individualized calligraphy course content is recommended for different students, and the weak points of each student's calligraphy course content are strengthened to educate and learn, so as to improve students' calligraphy ability. The application of this method greatly improves the students' interest in the course learning and the course achievement, and also enables teachers to accurately grasp the students' course learning situation. This provides guiding suggestions for the new teaching mode of calligraphy courses.

2. Theoretical Research Based on Deep Learning

In recent years, the technical application of deep learning has flourished, and deep learning can clearly capture the nonlinear relationship between users and items. This enables abstract representation of related data through deep networks. Not only that, it can additionally supplement the source of the data through text information, picture information, video and other information to make its content more accurate and rich [9]. Compared with other methods, related models built through deep learning often have better effects than other methods. This article would focus on the related theories about deep learning.

2.1. MLP Recommendation System

The MLP recommendation system mainly constructs a multi-layer hidden layer feed-forward neural network to describe the attribute relationship between students and courses [10]. There are two main models:

(1) NCF model

The NCF model is one of the most basic representations of the MLP model [11]. In this model, assuming a student A_i and course B_i, the Formula for students' preference for courses predicted by the NCF model is as follows:

$$\hat{m}_i = f(U^T A_i, V^T B_i | U, V, \delta) \tag{1}$$

Among them, f is the multi-layer neural network, and δ is the network parameter.

If it is to predict the grade of the course, then the loss function can be defined as the weighted squared difference, and its calculation Formula is as follows:

$$\tau = \sum_{i \in o \cup o^-} w_i (m_i - \hat{m}_i)^2 \tag{2}$$

In order to facilitate the calculation, we can also implement a binary system for the grades of the predicted courses [12]. Then $\hat{m}_i$ can be expressed as a probability distribution function, let the function value result in the [0,1] interval, and its loss function can be defined as cross entropy, and its expression is as follows:

$$\sigma = \sum_{i\in o \cup o^-}(m_i \log \hat{m}_i + (1 - m_i) \log 1 - \hat{m}_i) \tag{3}$$

If there is a data set, and it is assumed that there are a large number of unobserved interactions between students and courses, the NCF model can use negative sampling to increase the efficiency of training [13]. The NCF model structure can be shown in Figure 1:

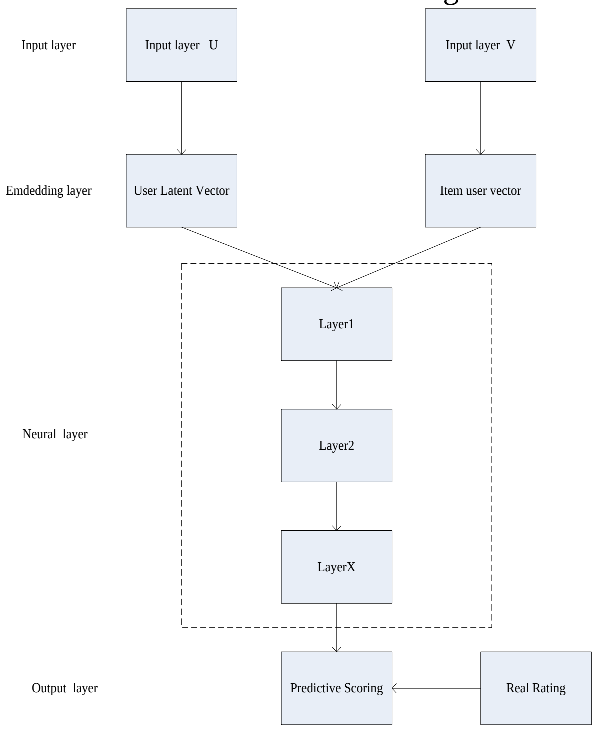

Figure 1. NCF model flow chart

As can be seen from Figure 1, the NCF model only needs to use matrix decomposition to obtain the expression of the implicit features of students or courses after dimensionality reduction, and does not require specific student-course feature solutions [14].

(2) Wide & Deep Learning model

The Wide & Deep Learning model is mainly divided into two parts: wide learning and deep learning. The width learning part can be approximated as a linear model, while the deep learning part is a multilayer perceptron [15]. The breadth learning part of the model can express the interaction between features in the historical information data, so that the model can remember that students have a certain degree of preference for a certain aspect of the course content. The deep learning part can abstractly express the relationship between students and courses, and finally achieve generalization [16].

In response to the previous description, we express the theory of the two parts of the model, where the expression of the width learning part is as follows:

$$y = K_{wide}\{x, \emptyset x\} + b \tag{4}$$

Among them, K_{wide} and b are the parameters of the model, and $\{x, \emptyset x\}$ is the set of characteristics.

The expressions for each layer in the deep learning part are as follows:

$$m^{i+1} = f\left(K^i_{deep} m^i + b^i\right) \tag{5}$$

Among them, i is the number of deep learning layers, f is the activation function, and K_{deep}^{i} and b^{i} are the parameters and biases of the i-th layer.

By deforming Formulas (4) and (5) accordingly, we can obtain the scoring prediction Formula of the Wide & Deep Learning model. The calculation Formula is as follows:

$$Y(\widehat{m}_i = 1|x) = \sigma\left(K_{wide}\{x, \emptyset x\} + K_{deep}^{i} m^{last} + bias\right) \tag{6}$$

Among them, σ is the sigmoid function, $\widehat{m}_i$ is the predicted value, and m^{last} is the activation value output by the last layer.

After some discussions on the Wide & Deep Learning model, we can conclude that the biggest advantage of this model is that it can make full use of the rich features of the student-course for modeling design, thereby improving the stability of modeling. This is mainly applicable to situations with richer knowledge areas or auxiliary features in the course, as well as in-depth knowledge of the professional discipline.

2.2. Automatic Encoder Recommendation System

Autoencoder recommendation systems generally use autoencoders to obtain low-dimensional representations of features or directly predict blank parts of the prediction matrix at the reconstruction layer [17].

(1) CFN model

The CFN model is improved to a certain extent on the basis of the traditional auto-encoder model. The observed fraction of each student's grades on the course is used as the input layer. The reconstruction work is completed in the output layer part, which effectively overcomes the negative impact of cold start and data sparse characteristics on model quality [18]. When observing students' grades on courses, there may be missing grade observations for some courses. In this case, we generally use masking noise to deal with it [19].

Assuming that there is an x^{j} containing noise as the input value, the calculation Formula of the loss function is as follows:

$$\theta = \gamma\left(\sum_{j\in J(A)\cap J(B)}\left(h\left(\hat{x}^{j}\right) - x^{j}\right)^{2}\right) + \mu\left(\sum_{j\in J(A)\setminus J(B)}\left(h\left(\hat{x}^{j}\right) - x^{j}\right)^{2}\right) + \varphi * \text{Regularization} \tag{7}$$

Among them, J(A) and J(B) are the index values of the observed normal and post-imitation courses, respectively. γ and μ are two hyperparameters, which are used to balance the influence of these two parts on the loss value, and $h\left(\hat{x}^{j}\right)$ represents the output value after the reconstruction of the input after adding noise.

On this basis, we can add the corresponding auxiliary information to fill the model, so that the training speed of the model is faster. The resulting reconstructed output value expression is as follows:

$$y\left(\hat{x}^{j}, r\right) = f\left(W_2\left\{k\left(W_1\left\{x^{j}, r\right\} + \theta\right), r\right\} + b\right) \tag{8}$$

Among them, r is auxiliary information, and $\left(\hat{x}^{j}, r\right)$ represents the connection between $\hat{x}^{j}$ and r.

(2) CDAE model

Unlike the CFN model, the CDAE model mainly performs ranking prediction, and its input value is usually the observed r^{t} value of students' implicit responses to some courses. For example, 1 means that students like a certain course, and 0 means that students do not like a certain course. We can first mask and fring the input value, and then generate a probability $p(\hat{r}^{t}|r^{t})$ for the masked value according to the characteristics of the normal distribution, then the expression of the reconstructed output value is as follows:

$$y(\hat{r}^t) = f(W_2 g(W_1 \hat{r}^t + x_t + b_1) + b_2) \quad (9)$$

Among them, $x_t \in \mathbb{R}^k$ represents the parameter vector corresponding to the student node. For each student node, this parameter vector is unique. By minimizing the reconstructed error, the parameters in Formula (9) can be obtained, and the calculation Formula is as follows:

$$\mathrm{argmin}_{W_1,W_2,b_1,b_2,V} \frac{1}{N} \sum_{t=1}^{N} E_{p(\hat{r}^t|r^t)} \left[\tau\left(\hat{r}^t, y(\hat{r}^t)\right)\right] + \mu * \mathrm{Regularization} \quad (10)$$

Among them, the loss function τ is a logarithmic loss function or a squared loss function, which normalizes the parameters and bias by assuming the τ_2 norm.

In the previous description of the CDAE model, it can be seen that the model does not require artificial feature selection, and the disadvantage is that it cannot make full use of other features of students or courses, and can only recommend courses with the help of students' evaluation information. Not only that, when the CDAE model is trained, each update of its parameters needs to reconsider the course score, which wastes time and increases costs.

3. Design of Course Content Recommendation Model Based on Deep Learning

Chinese calligraphy with Chinese characters as the carrier is the cultural treasure of the country and the precious wealth of human civilization. Calligraphy education plays a vital role in the cultivation of students' writing ability and aesthetic ability and the improvement of students' cultural quality. In order to further inherit the knowledge of calligraphy culture, many schools have opened calligraphy education courses to teach students calligraphy theory and practice. There are many problems in the current teaching activities of calligraphy courses, such as the explanation of calligraphy theory in the teaching of many schools. The students' grasp of it is only the skin, and they do not have a deep understanding of the theoretical knowledge of calligraphy. Not only that, in the practice of calligraphy, teachers simply tell the students how to write Chinese characters, and the students are in a state of being half-understood about the structure of Chinese characters. The existence of these problems greatly affects the effect of calligraphy course teaching. Therefore, we propose a new course content recommendation model based on the theory of deep learning. In the process of calligraphy course teaching, an in-depth analysis of calligraphy course information related to students and teachers is carried out. According to the data analysis results, individualized course content recommendations are made to students for different problems in calligraphy learning, so that they can have a deep understanding of calligraphy knowledge, and finally achieve the purpose of calligraphy teaching.

3.1. IUNeu Model Design

The related course recommendation models based on deep learning were introduced earlier, but these models do not fully utilize the information of students and courses, and cannot extract and analyze the characteristics and connections between students and courses from multiple perspectives. On this basis, we have made corresponding improvements to the previous course recommendation model, adding conditions such as auxiliary information to maximize the utilization of student-course information. The IUNeu model takes into account not only the ID information of students and courses, but also key information other than ID information. Taking students as an example, students' age, grade, etc. are added to the model as input values, while courses can be subdivided, such as course major categories and course minor categories [20]. All in the whole model, the input layer of the IUNeu model is [student, female, sophomore,...], [calligraphy course, hard pen teaching, soft pen teaching,...].

The IUNeu model absorbs the linear and nonlinear modeling capabilities of GMF and MLP, and incorporates student-course auxiliary information. For this, we simply deform and process the Formulations of GMF and MLP. Assuming that the latent feature vectors of students and courses are a_i and b_j, respectively, their related expressions are as follows:

$$\sigma(a_i, b_j) = a_i \otimes b_j \tag{11}$$

$$\hat{y}_p = k_{out}(x(\sigma)) \tag{12}$$

$$\begin{cases} m_1 = \sigma(a_i, b_j) = \begin{bmatrix} a_i \\ b_j \end{bmatrix} \\ \ldots \\ m_L = M_L(w_L m_{L-1} + n_L) \\ \hat{y}_p = \delta(x m_L) \end{cases} \tag{13}$$

Among them, $\otimes$ is the element-wise product between vectors, $\hat{y}_p$ is the predicted output value, and k_{out} is the activation function of the output layer. x is the weight of the output layer, and m_L, n_L, and w_L are the activation function, bias vector, and weight matrix of the Lth layer, respectively.

With the help of Formulas (11)(12)(13), we added the student-course auxiliary information on this basis, and obtained the Formula of the IUNeu model, and its expression is as follows:

$$L^{GMF} = (p_0^{GMF} \oplus p_1^{GMF} \oplus \ldots) \otimes (q_0^{GMF} \oplus q_1^{GMF} \oplus \ldots) \tag{14}$$

$$L^{MLP} = M_L\left(w_L\left(M_{L-1}\left(\ldots M_2\left(w_2\begin{bmatrix} p_0^{MLP} \oplus p_1^{MLP} \oplus .. \\ q_0^{MLP} \oplus q_1^{MLP} \oplus \ldots \end{bmatrix} + n_2\right)\ldots\right)\right) + n_L\right) \tag{15}$$

$$\hat{y}_p = \delta\left(x\begin{bmatrix} L^{GMF} \\ L^{MLP} \end{bmatrix}\right) \tag{16}$$

Among them, p_n^{GMF} and p_n^{MLP} are the student ID of the above model and the latent feature vector of auxiliary information, respectively, and the symbol $\oplus$ indicates that the original student or course ID (1, x) vector is expanded into a (1, y, x) matrix through attributes. x is the length of the feature vector and y is the length of the input vector.

3.2. Teaching Design of Calligraphy Course

In the current teaching of calligraphy courses, many schools use the online and offline co-teaching model to educate students in calligraphy courses, and the online and offline mixed teaching concentrates the advantages of both. Online teaching makes up for the disadvantage that offline teaching is limited by time and place. At the same time, offline teaching also shows the characteristics of interactive teaching. The combination of the two makes students' learning methods of calligraphy more diversified. In the daily offline teaching of calligraphy courses, students' understanding of calligraphy theory is not deep enough in the process of learning calligraphy theory. In the theoretical teaching of calligraphy courses, teachers cannot grasp the students' learning status in time. When conducting online teaching, although the platform can record the students' entire learning situation about calligraphy courses, it cannot conduct in-depth analysis of the information between students, courses and teachers. The existence of these problems affects students' calligraphy course learning and teachers' teaching effect.

When conducting online and offline teaching, we can record the problems encountered by students in the learning of calligraphy courses through online teaching.

Information about students and calligraphy lessons are then fed into the IUNeu model. Through the data analysis of the IUNeu model, it is found that when each student is studying the calligraphy course, there are problems such as insufficient cognition in some aspects of the calligraphy course.

Based on these analysis results, individualized content recommendations are made for each student's weak points in the process of learning calligraphy, so as to make up for the deficiencies in the learning of calligraphy. In this process, teachers can also understand the learning situation of each student's calligraphy course and the shortcomings of their own teaching content in calligraphy course teaching. Then, based on these analysis results, the teaching improvement of course content is carried out in a targeted manner, so as to facilitate the subsequent learning and teaching of calligraphy courses. When students lack knowledge of calligraphy theory, they can recommend content related to their calligraphy curriculum theory to fill in the gaps. Instead of purely theoretical teaching, people can use online resources to implement video teaching, so that students can deepen their impression of theoretical knowledge while watching middle school.

4. Experiment Demonstration of Calligraphy Course Teaching under Deep Learning

In the teaching of calligraphy courses, students need to understand the origin of Chinese characters, the structure of Chinese characters, and the stroke order structure of Chinese characters. Only by truly understanding Chinese characters can they acquire good calligraphy. In order to verify the effect of deep learning in calligraphy teaching, this paper selects the third grade students of school A as the experimental objects and divides them into the experimental group and the control group. The control group was taught the traditional calligraphy course, and the experimental group was taught the new calligraphy course based on deep learning. In the whole calligraphy course learning, real-time analysis is carried out for each student's calligraphy course learning situation, and relevant content recommendations are implemented for each student's course weak points to make up for the shortcomings of weak points. In the whole calligraphy course teaching, the main contents of the calligraphy, such as the essentials of holding the hard pen and the writing brush, the writing posture, the method of using the pen, the feeling of the pen, are taught. After the teaching of the calligraphy course is completed, the students of the two groups would be tested on the content of the calligraphy course, and the teaching effect of the two different modes would be judged by the content of the course.

4.1. Difference Test of Experimental Objects

We performed a T-test on the two groups, and the results are shown in Table 1.

Table 1. T-test for different learning abilities between subjects

Groups		Student's foundation	Learning efficiency	Learning ability	Students' own qualities
Control group	5	76.13 ± 2.16	75.93 ± 2.12	76 ± 2.03	76.1 ± 1.95
Experimental group	5	76.8 ± 2.21	76.6 ± 1.92	76.73 ± 1.94	76.87 ± 1.73
P		> 0.05	> 0.05	> 0.05	> 0.05

From Table 1, the experimental students of the two groups were found to be greater than 0.05 by independent sample T-test in terms of students' foundation, learning efficiency, understanding ability and students' own quality. It is concluded that there is no significant difference between the two groups, which indicates that the selected experimental objects meet the experimental requirements, and then experimental teaching activities can be carried out.

4.2. Course Content under Different Teaching Modes

(1) Test of students' mastery of calligraphy knowledge and teachers' teaching effect

The effect of calligraphy course teaching not only depends on students' mastery of calligraphy course content, but also depends on students' performance in calligraphy course learning to a large extent. A good classroom performance can increase students' cognition of calligraphy knowledge, and a solid calligraphy curriculum theory would provide a good effect on calligraphy practice. To this end, we tested the calligraphy knowledge mastery ability and teaching effect of the two groups under different modes, and the results of their calligraphy knowledge mastery ability are shown in Table 2 and Figure 2:

Table 2. Comparison table of students' mastery of the calligraphy curriculum under the two models

		Contents				
		A. The Origin of Chinese Characters	B. The construction of Chinese characters	C. Strokes of Chinese characters	D. Morphological evolution of Chinese characters	E. Chinese character dot painting
	Level of mastery					
Control group	Don't know	5	4	2	8	6
	Learn about	8	10	12	7	8
	Familiar	2	1	1	0	1
	Mastery	0	0	0	0	0
Experimental group	Don't know	1	0	0	2	0
	Learn about	10	11	12	10	10
	Familiar	3	3	0	2	3
	Mastery	1	1	3	1	2

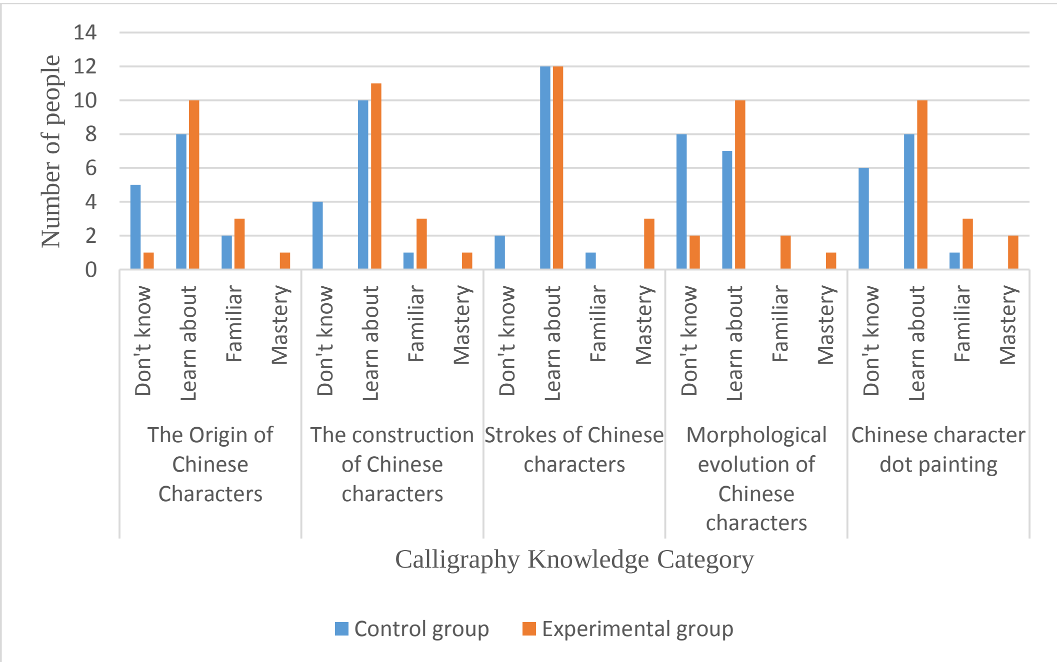

Figure 2. Comparison chart of students' mastery of the calligraphy curriculum in the two modes

Combining Table 2 and Figure 2, it can be seen that in terms of the origin of Chinese characters, the number of students in the experimental group above the understanding level is 4 more than that in the control group. In terms of the structure of Chinese characters, the number of students in the two groups in terms of content understanding of the structure of Chinese characters is not much different, but the number of students in the control group who do not understand is 4 higher than that in the experimental group. In terms of strokes of Chinese characters, the experimental group had 3 more strokes than the control group, while no one in the control group had mastered the strokes. In terms of the physical evolution of Chinese characters, the number of people in the control group who did not understand is much higher than that in the experimental group, and the number of people in the experimental group who are familiar with and mastered is much higher than the control group, with 3 more people. In the aspect of Chinese character pointillism, the number of people in the control group who did not understand the degree reached 6, while there was no one in the experimental group. We take the level of understanding as the passing line, and conduct statistical analysis on the number of people who have reached the passing line in the two different modes of teaching, and then calculate the passing rate. The result of the passing rate is shown in Figure 3:

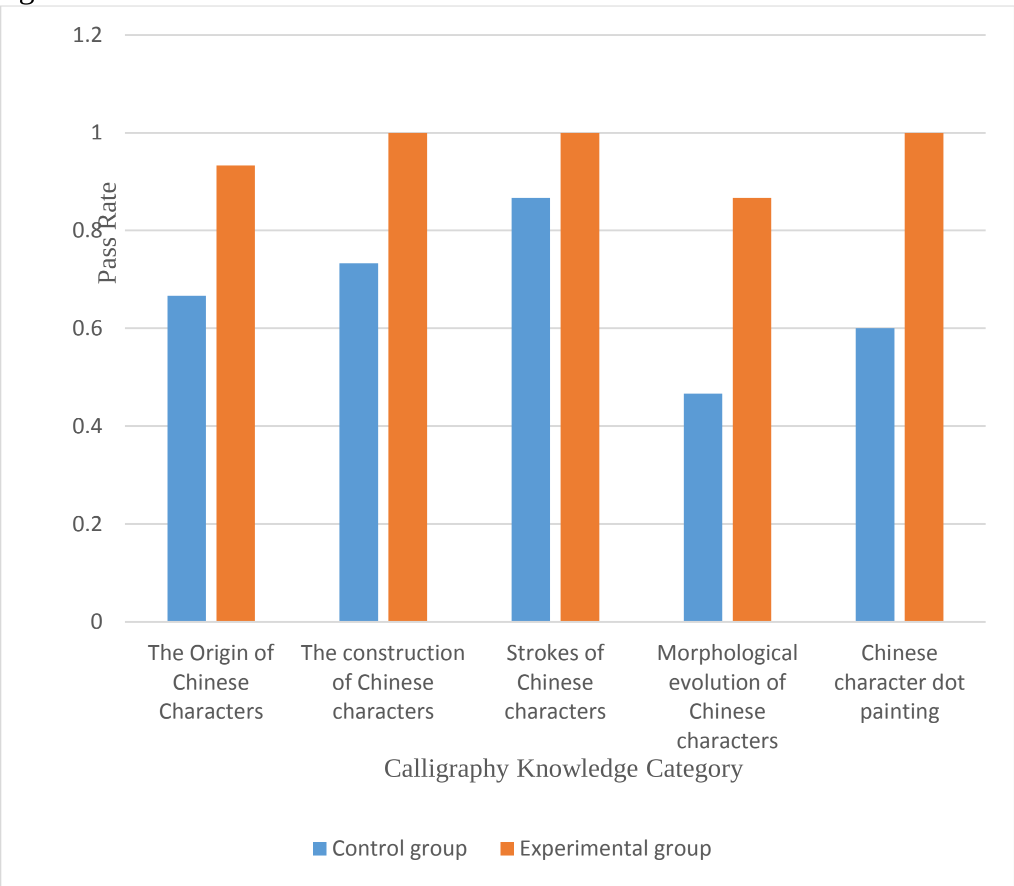

Figure 3. Comparison of the content pass rates of calligraphy courses under different teaching modes

It can be seen from Figure 3 that in the theoretical teaching of the five courses of calligraphy, the pass rate of the experimental group is higher than that of the students in the control group. Among them, in terms of the origin of Chinese characters, the structure of Chinese characters, the strokes of Chinese characters, the evolution of Chinese characters, and the stippling of Chinese characters, the pass rates of the students in the experimental group were 26.6%, 26.7%, 13.3%, 40%, and 40%

higher than those in the control group, respectively. This shows that the new calligraphy theory teaching under the in-depth learning is of significant help to students' learning of curriculum theory.

After completing the experimental teaching test of calligraphy theory, we carried out the teaching effect experiment of calligraphy course for the two groups, and the experimental results are shown in Table 3 and Figure 4:

Table 3. The effectiveness of teaching calligraphy courses in different modes（Percentage system）

		Control group	Experimental group	Difference in scores
Teaching effectiveness	Classroom feedback	68	85	17
	Classroom atmosphere	65	80	15
	Learning Status	60	82	22
	Learning outcomes	70	85	15

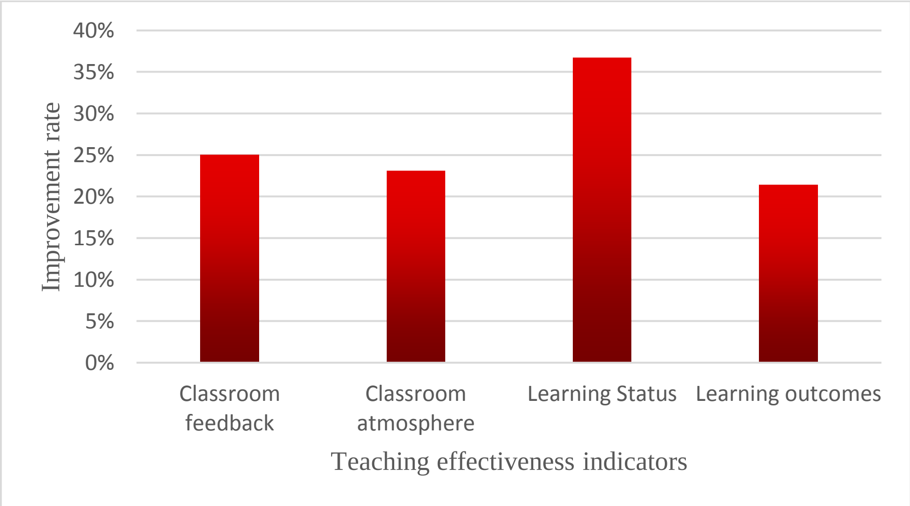

Figure 4. Comparison chart of the teaching effectiveness of calligraphy courses under different modes

Combined with Table 3 and Figure 4, the teaching effect of calligraphy course in the experimental group is higher than that in the control group in terms of classroom feedback, classroom atmosphere, student status and learning effect. Among them, the comprehensive score of the teaching effect of the experimental group was 332 points, and the comprehensive score of the teaching effect of the control group was 263 points, with a difference of 69 points. Compared with the control group, the improvement rates of the experimental group's scores in classroom feedback, classroom atmosphere, student status and learning effect were 25%, 23.1%, 36.7% and 21.4% higher, respectively. It shows that the teaching effect under deep learning is better than that under traditional mode.

(2) Comparative analysis of practical teaching of calligraphy courses

After the experimental teaching of calligraphy theory, we need to carry out practical teaching activities on calligraphy. This paper compares the use of hard brush and brush in calligraphy courses under two different teaching modes, which is to further compare the differences of calligraphy practice teaching under the two teaching modes. This paper mainly compares the four aspects of writing essentials, writing posture, writing method, and feeling of writing. The results are shown in Table 4 and Table 5:

Table 4. Comparison table of hard brush calligraphy under two different teaching modes

Groups		Strokes of the pen	Writing position	Stroke method	Feeling of the pen
Control group	5	81.4 ± 1.21	80.67 ± 1.38	81.6 ± 1.70	81.3 ± 1.34
Experimental group	5	87.1 ± 1.41	87.27 ± 1.34	87 ± 1.16	87.13 ± 1.36
P		< 0.01	< 0.01	< 0.01	< 0.01

Table 5. Comparison table of brush calligraphy under two different teaching modes

Groups		Strokes of the pen	Writing position	Stroke method	Feeling of the pen
Control group	5	81.7 ± 1.47	80.83 ± 1.86	80.5 ± 1.98	80 ± 1.48
Experimental group	5	83.3 ± 1.28	83.5 ± 1.19	83.1 ± 1.04	83.8 ± 1.59
P		< 0.05	< 0.05	< 0.05	< 0.05

Combining Table 4 and Table 5, it can be seen that after the teaching of the new type of calligraphy practice course, in terms of hard pen calligraphy and brush calligraphy practice teaching, the scores of the experimental group's writing essentials, writing posture, writing method, and feeling of writing have all improved. In the practice teaching of hard pen calligraphy, the p-values of the four practice indicators of the experimental group are all less than 0.01, indicating that the teaching effect of the new hard pen calligraphy practice course under deep learning is significant and extremely significant. In the practice teaching of brush calligraphy, the p-values of the four practice indicators of the experimental group were all less than 0.05. This shows that the teaching effect of the new brush calligraphy practice course under deep learning is remarkable. To further compare the teaching differences between the two groups, we conducted a comparative analysis of the data in Tables 4 and 5, and the results are shown in Figures 5 and 6:

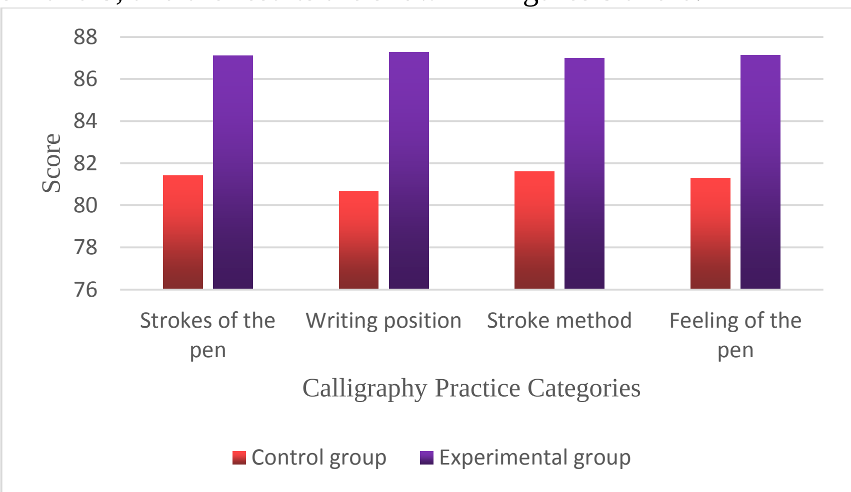

Figure 5. Comparison chart of hard brush calligraphy under two different teaching modes

As can be seen from Figure 5, the scores of the students in the experimental group are much higher than those in the control group in terms of writing essentials, writing posture, writing method, and writing feeling. Among them, the scores of writing essentials, writing posture, writing method and feeling of writing were higher than those of the control group by 5.7, 6.6, 5.4 and 5.83 points respectively. It shows that after the teaching of calligraphy practice course under deep learning, the effect of students' hard pen practice course is remarkable.

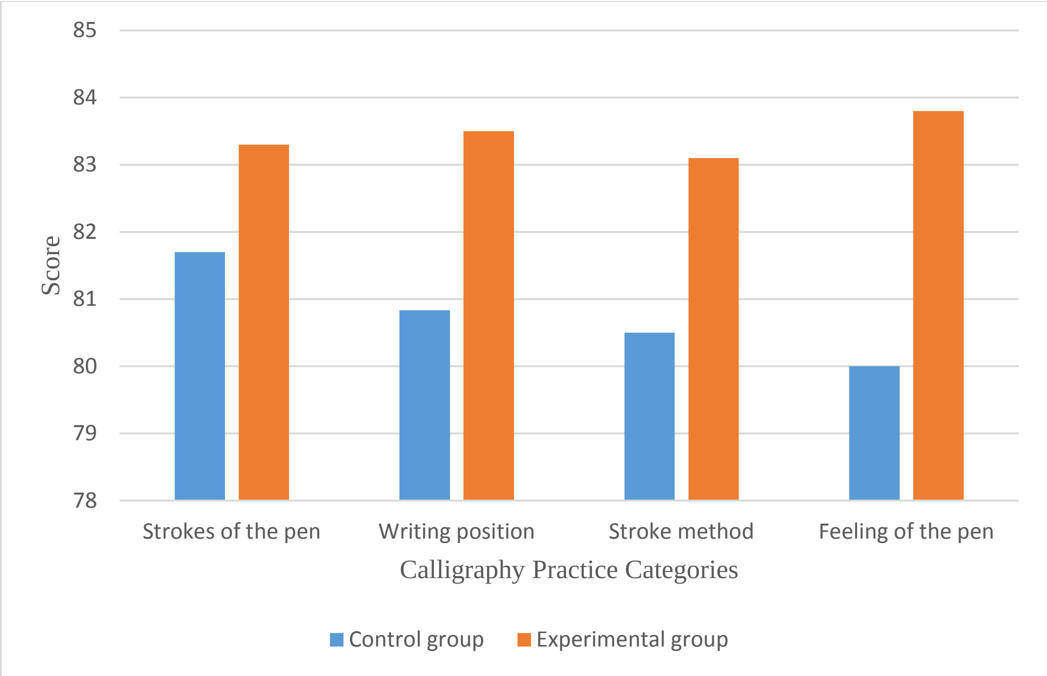

Figure 6. Comparison chart of brush calligraphy under two different teaching modes

As can be seen from Figure 6, the scores of the students in the experimental group are much higher than those in the control group in terms of writing essentials, writing posture, writing method, and writing feeling. Among them, the scores of writing essentials, writing posture, writing method, and feeling of writing are higher than the control group by 1.6 points, 2.67 points, 2.6 points and 3.8 points respectively. It shows that after the teaching of calligraphy practice course under in-depth learning, the effect of students' brush practice course is remarkable.

4.3. Teaching Purpose of Calligraphy Courses under Different Modes

The purpose of opening calligraphy courses in schools is not simply to carry out theoretical teaching and practical teaching of calligraphy courses, but teachers to teach students the knowledge related to calligraphy courses. It allows students to apply these knowledge to their own strengthening, and strive to improve their calligraphy ability and calligraphy appreciation ability. Through the study of calligraphy courses, this has improved his ability to a certain extent. In order to further explore the real situation of students' calligraphy course study under different modes, we used the question-and-answer test to understand the achievement of the two groups of students' calligraphy ability and calligraphy appreciation ability. The experimental results are shown in Figure 7 and Figure 8:

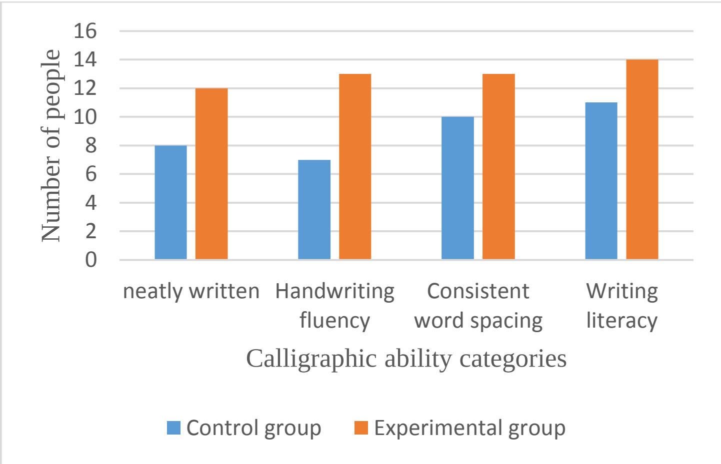

Figure 7. Comparison chart of calligraphic capabilities in different modes

It can be seen from the Figure 7 that after the calligraphy course teaching under deep learning, the students' calligraphy ability has been improved.

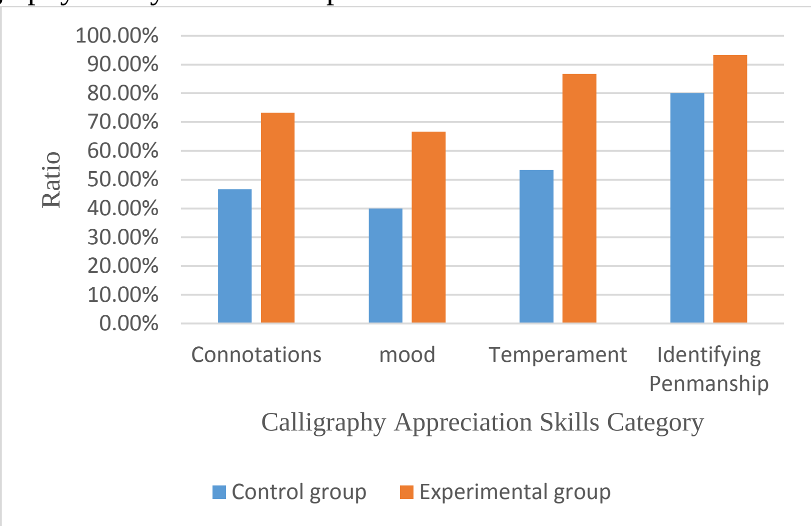

Figure 8. Comparison chart of appreciation of calligraphy in different modes

As can be seen from Figure 8, the proportion of students in the experimental group in the four calligraphy appreciation abilities of connotation, artistic conception, temperament, and distinguishing strokes is higher than that in the control group. Their proportions were 26.6%, 26.7%, 33.4% and 13.3% higher respectively, indicating that after the calligraphy course teaching under in-depth learning, students' calligraphy appreciation ability has been improved.

5. Conclusion

In recent years, due to the impact of the epidemic, students' course learning has been affected to a certain extent, and many schools have carried out online and offline hybrid teaching. To a large extent, it has achieved certain results, but its teaching effect and quality are far from the ideal expectations. In this context, based on deep learning theory, this paper proposed improvements to the current online-offline blended teaching model, and conducts an experimental comparative analysis of the improved teaching model, and the results achieve the expected results. The main research work of this paper was divided into the following three points:

(1) Theoretical research on deep learning

This part mainly introduces and explains the related theoretical research of deep learning. The MLP recommendation system and the automatic coding machine recommendation system are introduced successively, and several models in these two systems are introduced in detail to understand the application scope of the models.

(2) Design of course content recommendation model based on deep learning

This part mainly introduces the concept of auxiliary information on the basis of the previous relevant theoretical research to supplement the student-course information. The IUNeu course content recommendation model is proposed, and a series of introductions are made to the improvement of the blended teaching model.

(3) Experiment demonstration of calligraphy course teaching based on deep learning

This part mainly applies the IUNeu course content recommendation model to the current calligraphy course teaching, and compares and analyzes the traditional teaching mode and the improved teaching mode. This paper conducts experimental demonstration and analysis from three angles of calligraphy theory course teaching, calligraphy practice course teaching and calligraphy ability. According to the experimental results, it is concluded that the effect of the new calligraphy teaching mode is remarkable.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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