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Article

Research on the Innovation of English Teaching Mode in Colleges and Universities by Integrating Deep Learning Algorithms

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Abstract: In this paper, a new personalized recommendation system for English teaching resources is designed on the basis of deep learning, and a personalized English teaching model is innovatively proposed. The features of test information are continuously mined by convolutional neural network. Matrix decomposition technology and Bayesian criterion are adopted, so as to effectively characterize the association between users and English teaching resources, thus completing the recommendation of teaching resources. With the help of questionnaire data, the current status of the teaching practice of the Civics Smart Classroom in colleges and universities is understood. The test results show that the average test scores (P=0.001) and the degree of knowledge mastery (P=0.0045) of the experimental class and the control class are significantly different, indicating that the implementation of the personalized teaching mode based on the deep learning recommendation algorithm is effective. After the teaching practice, the students' independent learning, critical thinking, innovative thinking, problem solving, transfer thinking, effective communication, and cooperation ability are improved to different degrees.

Keywords: deep learning; personalized recommendation; matrix decomposition; teaching resources

1. Introduction

With the continuous development of modern information technology, the informatization of China's higher education sector has entered a completely new stage of development. Digital technologies such as big data, the Internet of Things and artificial intelligence have been deeply integrated with the teaching of specialized disciplines in colleges and universities, and the classroom teaching environment has undergone significant changes. In the process of comprehensively promoting "Internet + education" and striving to create a new form of digital education, the learning purpose and teaching concept of English courses in colleges and universities will also change [1]. In the past, the learning purpose of the English classroom mainly stayed in the shallow level of literacy, mimeography and understanding of English subject knowledge, while in the college English smart classroom, more attention is paid to the transformation of higher-order abilities to deep learning, such as the transfer of knowledge application, solving complex problems, and reflection and evaluation of the teaching process, etc. [2-3]. By constructing an innovative teaching model, teachers can create a harmonious teaching environment that supports deep learning in the smart classroom, thus stimulating students' enthusiasm for independent learning, promoting students' deep learning and thinking development, and improving students' learning effect and thinking ability [4-5]. Therefore, whether or not to accurately construct the deep learning mode and conduct scientific evaluation in the English smart classroom in colleges and universities has become an important measure to improve the quality of talent cultivation in Chinese universities. Targeted strategies should be adopted to address the problems of students' low motivation to participate, poor cognitive ability and cultivation effect that exist in the teaching of college English smart classroom at the present stage, in order to build a new smart classroom deep learning mode.

Intelligent teaching environment is a prerequisite to ensure the high quality of English intelligent classroom teaching activities in colleges and universities, and some scholars have explored the application of intelligent algorithms in intelligent English teaching classroom. Literature [6] constructs an English informative learning platform combining radial basis function (RBF) algorithm and neural network model, emphasizing the students' main position in the teaching process, stimulating the students' enthusiasm for English learning, and playing a powerful auxiliary role in English teaching. Literature [7] shows that computer intelligence algorithms are widely used in the design of English teaching systems, and proposes the LCAM model for improving students' English performance, which can optimize teachers' teaching strategies according to the information of students' characteristics in a targeted manner and provide a new perspective for the innovative development of English teaching mode. Literature [8] proposes an English grammar error correction model based on seq2seq algorithm, whose reliable error correction accuracy plays an important role in English teaching. Literature [9] utilizes a deep belief network-based speech recognition system to establish an evaluation model for the quality of college students' spoken English pronunciation, which provides technical support for improving the efficiency of spoken English teaching. The described deep learning intelligent algorithm greatly enriches the teaching content and teaching methods in English education in colleges and universities, stimulates students' learning enthusiasm and subjective initiative through flexible and scientific teaching design, and cultivates their higher-order thinking ability.

In addition, considering that the traditional English teaching assessment methods are relatively single, a large number of scholars have utilized intelligent algorithms to improve the assessment methods of English teaching effectiveness in colleges and universities. Literature [10] introduces particle swarm optimization algorithm to classify the factors affecting the quality of English teaching in colleges and universities, and combines the hierarchical analysis method to correct the influence weight of each factor layer by layer in order to reduce the interference of subjective factors. Literature [11] incorporates differential evolutionary algorithm to establish a teaching quality evaluation system with adaptive adjustment ability, and realizes a more objective, comprehensive and accurate evaluation of English teaching quality in colleges and universities by dynamically adjusting the weights of indicators. Literature [12] adopts the genetic algorithm based on grey association to optimize convolutional neural network and applies it to English teaching evaluation, which effectively gets rid of the subjectivity and unpredictability of the traditional evaluation methods, and improves the reliability of teaching quality evaluation. Literature [13] established a teaching quality evaluation model based on the sparrow search algorithm deep recurrent neural network algorithm, which can fully extract and retain the valuable features of the data, and accurately evaluate the quality of English teaching in colleges and universities. It can be found that in the practice of teaching evaluation combined with particle swarm optimization, differential evolution, genetic algorithm and sparrow algorithm and other intelligent algorithms of college English teaching effectiveness evaluation method, can effectively avoid the evaluation process by the influence of external factors of teaching, and then improve the effectiveness of the evaluation results. Therefore, constructing a deep learning mode of college English smart classroom is of great significance in promoting students' diversified development and improving the quality of English learning.

Aiming at the informatization needs of English teaching in the new era, combined with the deep learning recommendation algorithm, this paper proposes an English teaching system based on personalized recommendation. Frameworks such as Spring are utilized to design the functions, physical architecture, and technical architecture of the system, and focus on the intelligent recommendation module. CNN is used to mine the potential features of teaching resource data, generate the implicit feature vectors of test questions, and construct the implicit feature matrix of test questions with weight parameters. The joint probability matrix decomposition of the implicit feature matrix of test questions is performed by matrix decomposition technique. This study applies the personalized English teaching model based on deep learning to English classroom teaching, and uses questionnaire survey and comparative experimental method to explore its teaching effect.

2. Personalized teaching model based on recommendation algorithms

2.1. The Design of English Teaching System with Personalized Recommendations

With the current application of computer informatization in teaching, various kinds of English auxiliary teaching systems have emerged. These auxiliary teaching management systems not only promote the application of information technology in teaching, but also promote the sharing of English teaching resources. Taking the campus network as the basis and adopting the idea of network layering, the auxiliary teaching system that can be used for English learning has been constructed, so that the students of colleges and universities can complete their English learning through the campus network. Personalized recommendation algorithm, as a widely used intelligent algorithm, is widely used in e-commerce, hobbies and so on. In this regard, combined with the drawbacks of the English auxiliary teaching system, the recommendation algorithm is introduced on the basis of the design of the traditional auxiliary teaching system, and then through the construction of this paper, it expands the practicability of the current teaching system and better provides services for English learning.

2.2. System architecture design

The platform building of this system is realized using Java language for development, JDK version 1.8, and the development process uses Eclipse as the development tool. Among them, the core algorithm is implemented using python language. The system is designed in B/S mode, using Spring and other frameworks to realize the system development. The information of the system experimental platform is described as follows.

The system follows the standard three-layer architecture pattern shown in Figure 1.

Representation layer: The representation layer is the front-end interface that users see and can interact with the system. The pages designed in this system include the login interface, the main interface, the practice center, and the learning situation analysis.

Business Logic Layer: Business Logic Layer is located in the middle of Representation Layer and Data Access Layer, which is responsible for processing the data read from the database and then transferring them to the platform interface that users can see. The business logic layer of this system consists of information management, recommendation module and data analysis and processing.

Data access layer: The data access layer is mainly responsible for reading and modifying the data table information in the database and transferring it to the business logic layer, and at the same time, saving the operation data of the business logic layer to the database. The data tables involved in this system mainly include the student information table, the test question information table and the student record information table.

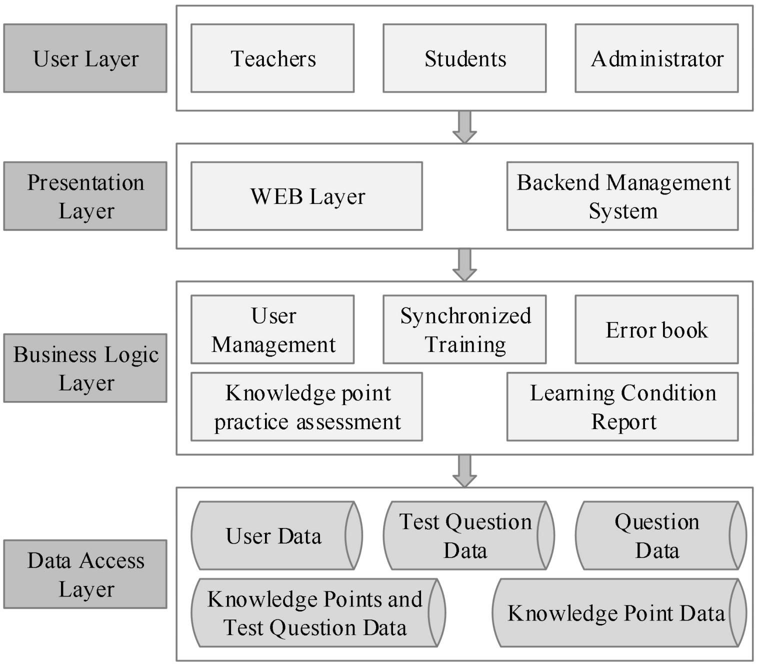


Figure 1. Three-tier schema

The core function of this system is Knowledge Points and Test Questions Recommendation Module, which uses relational database MySQL to save the data.E-R diagram provides the methods of entity types, attributes and relationships in the core module of this system. By analyzing the E-R diagram of Knowledge Points and Test Questions Recommendation Module, the main data tables are obtained including Student Information Table, Test Questions Information Table, Knowledge Points Information Table, Student Doing Record Information Table, Knowledge Tracking Model Table and Algorithm Results Table.

2.3. System Function Module Design

The personalized test question recommendation system developed in this paper consists of three modules, namely teacher module, student module and administrator module. Teacher module, teachers through the system login page to correctly enter my account and password, click the login button to enter their own teacher module. The main functions of this module include personal information management, posting exercises, online grouping of papers and viewing of learning status. Teachers can post exercises for students to practice after class or for homework during vacation. Teachers can also organize papers manually or online for after-class testing. For student module, students can enter their account and password correctly through the system login page and click the login button to enter their own learning module. The main functions include personal information management, synchronized exercises, knowledge assessment exercises, wrong questions and learning situation analysis. Administrator module, the administrator through the background of the system within the school teacher account and student account information for daily management, including adding and assigning the system account to the school teachers and students, and set up different user login privileges.

2.4. Intelligent Recommendation Module Design

2.4.1. Deep Learning Convolutional Network Framework

With the continuous development of deep learning technology, convolutional neural network has been widely used by researchers, and its effect has been well verified in many network models. Convolutional neural networks (CNNs) can not only deeply mine video text and other modal data information from different dimensions, but also the operation of the convolution is mainly to enhance the machine learning system through the characteristics of parameter sharing, sparse weights, and variability such as translation.

The convolutional network framework of CUPMF model consists of the following four layers:

(1) Word embedding layer

The word embedding layer converts the original test question information into a dense numeric matrix as the input to the next convolutional layer. Specifically, the test question information mainly contains three parts: test question stem, test question answer and test question paraphrase, these three parts are processed by the word splitting technique, and each word is converted into a word vector either by means of random initialization value or by the pre-training word embedding model, and finally, the test question is represented as a dense numeric matrix $T_j \in R^{p \times l}$ by connecting the word vectors in the test question information as shown in Equation (1). Where p is the dimension of the vector and l denotes the number of word vectors:

$$T_j = \begin{bmatrix} & | & | & | & \\ \cdots & w_{i-1} & w_i & w_{i+1} & \cdots \\ & | & | & | & \end{bmatrix} \tag{1}$$

(2) Convolutional layer

The convolutional layer is mainly used to extract the feature information of the test questions, the nature of the test question feature information is different from the contextual information of pictures, audio or video, which requires some modifications to the convolutional network to be suitable. A test question context feature $c_i^j \in R$ is extracted by the j nd shared weight $W_c^j \in R^{p \times w}$, whose window size w represents the number of surrounding words, i.e., it satisfies equation (2):

$$c_i^j = fun\left(W_c^j \otimes D_{(i:(i+w-1))} + b_c^j\right) \tag{2}$$

Then, the contextual feature vector $c^j \in R^{l-w+1}$ with weight W_c^j is constructed by Eq. (2) as shown in Eq. (3):

$$c^j = \left[c_1^j, c_2^j, \ldots, c_i^j, \ldots, c_{l-w^+ +1}^j\right] \tag{3}$$

(3) Pooling layer

After the matrix composed of test word vectors is convolved by the convolution operation, the test information is represented as a n_c -level dimension feature matrix, and the dimensions of the test feature vectors in the matrix are not uniform, i.e., the number of matrix columns is not uniform. This model extracts representative features from each test question feature vector by pooling layer and reduces the representation of the test question document to n_c fixed-length feature vectors by constructing fixed-length feature vectors by subsumption operation as shown in equation (4):

$$d_f = \left[\max\left(c^1\right), \max\left(c^2\right), \ldots, \max\left(c^j\right), \ldots, \max\left(c^{n_c}\right)\right] \tag{4}$$

(4) Output Layer

In the output layer is mainly responsible for making a nonlinear mapping of the output of the previous layers. Therefore, it is necessary to map d_f on the k -dimensional space of the joint probability matrix decomposition model to accomplish the recommendation task, i.e., generating the trial latent matrix by using the regular nonlinear mapping as shown in Equation (5).

$$D_j = \tanh\left(W_{f_2}\left\{\tanh\left(W_{f_1} d_f + b_{f_1}\right)\right\} + b_{f_2}\right) \tag{5}$$

where $W_{f_1} \in R^{f \times n_c}$ and $W_{f_2} \in R^{k \times f}$ are the mapping matrices, and b_{f_1} and b_{f_2} are the deviation vectors of W_{f_1}, W_{f_1} and $D_j \in R^k$.

Finally, through the convolution and nonlinear transformation processing of the above layers of hidden layers, the convolution part of the CUPMF model is approximately intertwined into a nonlinear function, which takes the test word vectors as inputs, and the outputs are the implicit feature vectors corresponding to each test question as shown in Eq. (6):

$$D_j = Cnn\left(W, T_j\right) \tag{6}$$

2.4.2. Joint probability matrix decomposition

The main idea of the joint probability matrix decomposition part of the CUPMF model is to decompose the student-test score information matrix, the student-knowledge point mastery matrix, and the test-knowledge point relationship matrix manually recorded by domain experts collected by the platform through the matrix decomposition technique, and then decompose the student implicit feature matrix, the knowledge point implicit feature matrix, and the test implicit feature matrix, which incorporate the weights and parameters. parameters, then, the original correlation information matrix is represented by Bayesian criterion, and the real correlation information matrix data is fitted after continuous training, so as to obtain the relevant parameters of each implicit feature matrix, and finally the trained implicit feature matrix predicts the performance of the students on the teaching resources, and the recommendation is made by combining the mastery of the students' -knowledge points.

The probability distribution of matrix D is obtained through the above equation as in equation (11):

$$p\left(U \mid \sigma_U^2\right) = \prod_{i=1}^{m} G\left(U_i \mid 0, \sigma_U^2 I\right) \tag{7}$$

$$p\left(K \mid \sigma_K^2\right) = \prod_{i=1}^{l} G\left(K_i \mid 0, \sigma_K^2 I\right) \tag{8}$$

$$p\left(W \mid \sigma_W^2\right) = \prod_{k} G\left(w_k \mid 0, \sigma_W^2\right) \tag{9}$$

$$D_j = Cnn\left(W, T_j\right) + \varepsilon_j \tag{10}$$

$$p\left(D \mid W, T, \sigma_D^2\right) = \prod_{j=1}^{n} G\left(D_j \mid Cnn\left(W, T_j\right), \sigma_D^2 I\right) \tag{11}$$

If student i has done test j, then $I_{ij}^R = 1$, otherwise $I_{ij}^R = 0$. $h(x)$ is a sigmoid function, i.e., it maps the value of $U_i^T Cnn\left(W, T_j\right)$ to the range $(0,1)$:

$$p\left(R \mid U, D, \sigma_R^2\right) = \prod_{i=1}^{m} \prod_{j=1}^{n} \left[G\left(r_{ij} \mid h\left(U_i^T Cnn\left(W, T_j\right)\right), \sigma_R^2 I\right)\right]^{I_{ij}^R} \tag{12}$$

The mathematical expression for its conditional probability distribution is shown in Equation (13). Where I_{ij}^{A} is the indicator function, $I_{ij}^{A}=1$ if student i has mastered knowledge point j, and $I_{ij}^{A}=0$ otherwise:

$$p\left(A \mid U,K,\sigma_A^2\right)=\prod_{i=1}^{m}\prod_{j=1}^{l}\left[G\left(\alpha_{ij} \mid h\left(U_i^T K_j\right),\sigma_A^2 I\right)\right]^{I_j^A} \tag{13}$$

Similarly, from the implicit eigenvector D_i of test question i and the implicit eigenvector K_j of knowledge point j, it can be obtained that: the association case q_{ij} of test question i and knowledge point j satisfies a Gaussian distribution with mean $h\left(Cnn\left(W,T_j\right)^T K_j\right)$ and variance σ_Q^2 and is independent, and its conditional probability distribution is shown in Equation (14). Where I_{ij}^{Q} is the indicator function, if test question i examines knowledge point j, then $I_{ij}^{Q}=1$.

Otherwise $I_{ij}^{Q}=0$:

$$p\left(Q \mid D,K,\sigma_Q^2\right)=\prod_{i=1}^{m}\prod_{j=1}^{l}\left[G\left(\alpha_{ij} \mid h\left(Cnn\left(W,T_j\right)^T K_j\right),\sigma_Q^2 I\right)\right]^{I_{ij}^Q} \tag{14}$$

Combined with the above equation of prior probability distribution, the posterior probability distribution of matrices U, D, W, and K can be obtained from the Bayesian criterion as shown in Eq. (15):

$$\begin{aligned} & p(U,D,W,K \mid R,A,Q,T,\sigma_U^2,\sigma_W^2,\sigma_D^2,\sigma_K^2,\sigma_R^2,\sigma_A^2,\sigma_Q^2) \\ &= p\left(Q \mid D,K,\sigma_Q^2\right)\cdot p\left(K \mid \sigma_K^2\right)\cdot p\left(D \mid W,T,\sigma_D^2\right) \\ &\cdot p\left(W \mid \sigma_W^2\right)\cdot p\left(R \mid U,D,\sigma_R^2\right)\cdot p\left(U \mid \sigma_U^2\right) \\ &\cdot p\left(D \mid W,T,\sigma_D^2\right)\cdot p\left(W \mid \sigma_W^2\right)\cdot p\left(A \mid U,K,\sigma_A^2\right) \\ &\cdot p\left(U \mid \sigma_U^2\right)\cdot p\left(K \mid \sigma_K^2\right) \end{aligned} \tag{15}$$

Bringing the above equation into Equation (15) taking logarithms on both sides gives Equation (16):

$$\begin{aligned} & \ln p\left(U,D,W,K \mid R,A,Q,T,\sigma_U^2,\sigma_W^2,\sigma_D^2,\sigma_K^2,\sigma_R^2,\sigma_A^2,\sigma_Q^2\right) \\ &= -\frac{1}{2\sigma_Q^2}\sum_{i=1}^{n}\sum_{j=1}^{l} I_{ij}^{Q}\left(q_{ij}-h\left(Cnn\left(W,T_i\right)^T K_j\right)\right)^2 \\ &-\frac{1}{2\sigma_R^2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}\left(r_{ij}-h\left(U_i^T Cnn\left(W,T_j\right)\right)\right)^2 \\ &-\frac{1}{2\sigma_A^2}\sum_{i=1}^{m}\sum_{j=1}^{l} I_{ij}^{A}\left(\propto_{ij}-h\left(U_i^T K_j\right)\right)^2-\frac{1}{2\sigma_U^2}\sum_{i=1}^{m} U_i^T U_i \\ &-\frac{1}{2\sigma_D^2}\sum_{j=1}^{n}\left(D_j-Cnn\left(W,T_j\right)\right)^2-\frac{1}{2\sigma_W^2}\sum_{i=1}^{|W_i|} W_i^T W_i \\ &-\frac{1}{2\sigma_K^2}\sum_{i=1}^{l} K_i^T K_i-\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}^{R}\ln\sigma_R-\sum_{i=1}^{m}\sum_{j=1}^{l} I_{ij}^{A}\ln\sigma_A \\ &-\sum_{i=1}^{n}\sum_{j=1}^{l} I_{ij}^{Q}\ln\sigma_Q-p\sum_{i=1}^{m}\ln\sigma_U-p\sum_{i=1}^{l}\ln\sigma_K \\ &-p\sum_{i=1}^{n}\ln\sigma_D-p\sum_{i=1}^{|W_i|}\ln\sigma_W+C \end{aligned} \tag{16}$$

where p denotes the dimension of the implicit feature vector and c is a constant. The maximization formula (16) can be regarded as an unconstrained optimization problem, which is equivalent to the minimization formula (17):

$$
\begin{aligned}
&E\left(U,D,W,K,R,A,Q\right)\\
&=\frac{\varphi_Q}{2}\sum_{i=1}^{n}\sum_{j=1}^{l}I_{ij}^{Q}\left(q_{ij}-h\left(Cnn\left(W,T_i\right)^T K_j\right)\right)^2\\
&+\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}I_{ij}^{R}\left(r_{ij}-h\left(U_i^T Cnn\left(W,T_j\right)\right)\right)^2\\
&+\frac{\varphi_A}{2}\sum_{i=1}^{m}\sum_{j=1}^{l}I_{ij}^{A}\left(\propto_{ij}-h\left(U_i^T K_j\right)\right)^2+\frac{\varphi_U}{2}\sum_{i=1}^{m}U_i^T U_i\\
&+\frac{\varphi_D}{2}\sum_{j=1}^{n}\left(D_j-Cnn\left(W,T_j\right)\right)^2+\frac{\varphi_w}{2}\sum_{i=1}^{|W_i|}W_i^T W_i\\
&+\frac{\varphi_K}{2}\sum_{i=1}^{l}K_i^T K_i
\end{aligned}
\tag{17}
$$

3. Effectiveness and analysis of teaching practices

3.1. Growth rate of online education users in China

The growth rate of online education users in China is shown in Table 1, in addition, the annual growth rate of mobile online education course users is mostly in the range of 10% to 15%, and the user scale has grown the most among all types of activities completed using cell phones. As of December 2023, China has 195 million mobile online education course users. In the context of advocating "Internet +" in the country, education informatization has been upgraded to the policy level of "building a strong country in education", and smart campuses and "Internet + education" are also included in the specific implementation plan, which means that the substantive policy benefits fall on online education. With the guidance of national policies and the development of information technology, the future development of China's education depends largely on smart education. The mobile Internet era facilitates daily life at the same time, but also produces a large amount of data and information, nowadays dazzling kinds of recommendation system, the vast majority of applications in the commercial field, compared with the education field recommendation system is relatively small. Under the double pressure of work and study, the realization of personalized recommendation of educational resources has become the primary problem of intelligent education. The application of personalized recommendation system can effectively solve the problem of cognitive overload or disorientation of users during online learning, and can greatly improve the utilization rate of resources and user learning efficiency. With the emphasis on personalized learning, personalized teaching based on deep learning recommendation algorithms provides a good opportunity.

Table 1. The list of users who use their mobile phones on the Internet

	2023	**2022**	
Applied	User size (Ten thousand)	User size (Ten thousand)	Annual growth rate
Instant phone communication	78135	69542	11.00%
Mobile search	65427	62405	4.62%
Mobile network news	65374	62063	5.06%
Mobile network shopping	59214	50574	14.59%
Mobile network video	58936	54866	6.91%
Mobile phone payment	58400	52814	9.57%
Mobile network music	55324	52284	5.49%
Mobile games	45923	40728	11.31%
Mobile Internet literature	41023	34368	16.22%
Mobile booking	40036	34012	15.05%
Order takeout on your mobile phone	40025	32230	19.48%
Mobile online education course	19528	11925	38.93%

3.2. Analysis of Instructional Design Application and Effectiveness

The study chooses to carry out teaching practice in a freshman class of X college in Y city, which has been carrying out smart classroom for more than a year and has mature equipment base. In order to better integrate the idea of instructional design with reality, this experiment adopts the experimental control method, in which two classes of the same grade with similar learning levels are selected in the internship school to carry out the experiment, and class A is taken as the experimental class, and class B is taken as the control class. The control class is still taught in the traditional way, and the experimental class is taught in the personalized teaching mode based on deep learning designed in this paper, in order to verify the teaching effect. In this section, the teaching practice of personalized teaching mode based on deep learning is designed from the aspects of experimental subjects, experimental variables and hypotheses, and experimental process, which will be elaborated in the following.

The experimental objects of this paper are Class A and Class B of X Middle School in Y City, the number of the two classes are 47 and 46 respectively, totaling 93 students. In order to grasp the difference between the two classes of students in the level of knowledge, the final results of the two classes of students in class A and class B and the average score of the two monthly exams for comparative analysis, the main reason is that these three exams are organized by the school for all grades of all students to participate in large-scale exams, the difficulty of the appropriate and the validity of the question paper topics and the reliability of the students' learning performance is high, so it will be used as a pre-test of experimental assessment criteria. The pre-test assessment scores of the students in the two classes are shown in Table 2, and it is found that the average scores of the two classes are very close to each other. It indicates that there is no significant difference in the average scores of the students in the two classes and a comparative experiment can be conducted.

Table 2. Student record

	Class	**Final grade**	**Monthly grade**	**Monthly grade**
Preexperiment	Laboratory class	52.56	52.41	52.63
	Cross-reference class	54.78	52.74	53.52

To ensure the authenticity and validity of the achievement test, the study chose to compare the experimental class with the control class. Before the implementation of the two classes, the two classes have the same level of performance in the monthly examination, the same teaching progress and the same teachers, after the experimental class model practice, the study collected and counted the monthly examination results of the two classes, after the completion of the data collection, the students' performance in the pre and post-tests were statistically analyzed, and the independent samples t-test was conducted on the data by using SPSS 24.0, and the results of the data analysis are shown in Table 3. Pre-test: to carry out independent samples T-test, first of all, the independent samples should be tested for chi-square, F = 0.664, Sig is 0.336 greater than 0.05, so the two samples are chi-square, independent samples T-test can be carried out, P is 0.811 greater than 0.05, so there is no significant difference in the results of the two classes.

Post-test: the same independent samples t-test for the data results, first of all, the independent samples should be tested for variance chi-square, F is 0.000, Sig is 0.872 is greater than 0.05, so the two samples are chi-square, independent samples t-test can be performed, $P=0.001<0.05$, so there is a difference in the results of the two classes, and, the experimental class's mean is slightly higher than that of the control class's mean value, which indicates that the implementation of the personalized teaching model based on deep learning is effective.

Table 3. The students' record

	Class	**N**	**M**	**SD**	**T**	**P**
Pretest	Laboratory class	50	52.63	20.204	-2.45	0.811
	Cross-reference class	50	53.52	18.393	-2.45	0.811
Posttest	Laboratory class	50	55.28	13.764	4.463	0.001
	Cross-reference class	50	53.72	13.245	4.463	0.001

3.3. Level of deep student learning

Based on the 5C scale and the Deep Learning Competency Scale, this study synthesized the conceptual connotation and characteristics of deep learning and compiled the Deep Learning Competency Questionnaire, which was designed from two first-level dimensions, namely, personal and interpersonal, for testing and evaluating students' level of deep learning, and the personal domain was divided into five dimensions: self-directed learning, critical thinking, problem solving, innovative thinking, and migratory thinking. The personal domain is divided into five dimensions: independent learning, critical thinking, problem solving, creative thinking and transfer thinking. The interpersonal domain is divided into the second-level dimensions of effective communication and cooperation ability.

Validity analysis is a measure of the validity of the questionnaire, because the research questionnaire borrowed from the mature scale so the validation factor analysis was carried out using SPSS24.0 software, the results are shown in Table 4, it can be seen that the KMO value of 0.874, which is greater than 0.6, indicating that this questionnaire has a high degree of validity, and it can be formally used.

In this study, the above questionnaire scale was put into use, and the questionnaire of "before and after class" was adopted for the experimental class, and the questionnaire before and after class was conducted. After cleaning and organizing the collected data and importing them into SPSS, the sample data were normally distributed and could be subjected to independent samples t-test. This study analyzes the deep learning level of the learners in two aspects, one is to analyze the personal domain, and the other is to analyze the interpersonal domain.

The results of the experimental group's deep learning questionnaire before and after the test were counted and assigned values, and the data were analyzed by SPSS24.0 for the independent samples t-test, and the average score of the experimental group's overall level of deep learning after the test was higher than that of the pre-test, and there was a significant difference. In the data analysis of the seven aspects of this questionnaire, namely, independent learning, critical thinking, innovative thinking, problem solving, transfer thinking, effective communication, and cooperation ability, all of them showed different degrees of improvement. Thus the deep learning state of the study participants was promoted under this teaching model.

Table 4. Independent sample T test

	Categories	M	SD	Sig.	Sig. (Double tail)	95% confidence interval	
						Lower limit	**Upper limit**
Autonomous learning	Pretest Posttest	3.563 4.175	0.341 0.514	0.01	0.12	-2.80	2.47
Critical thinking	Pretest Posttest	3.421 3.861	0.447 0.576	0.00	0.37	-2.43	2.24
Creative thinking	Pretest Posttest	3.522 4.243	0.631 0.574	0.06	0.02	-1.51	2.83
Problem solving	Pretest Posttest	3.576 4.206	0.431 0.486	0.01	0.13	-1.81	1.82
Migration thinking	Pretest Posttest	3.645 4.427	0.478 0.466	0.34	0.08	-2.66	1.64
Effective communication	Pretest Posttest	3.563 3.902	0.432 0.557	0.03	0.02	-1.63	2.52
Cooperation ability	Pretest Posttest	3.728 4.425	0.472 0.451	0.11	0.04	-1.81	2.73

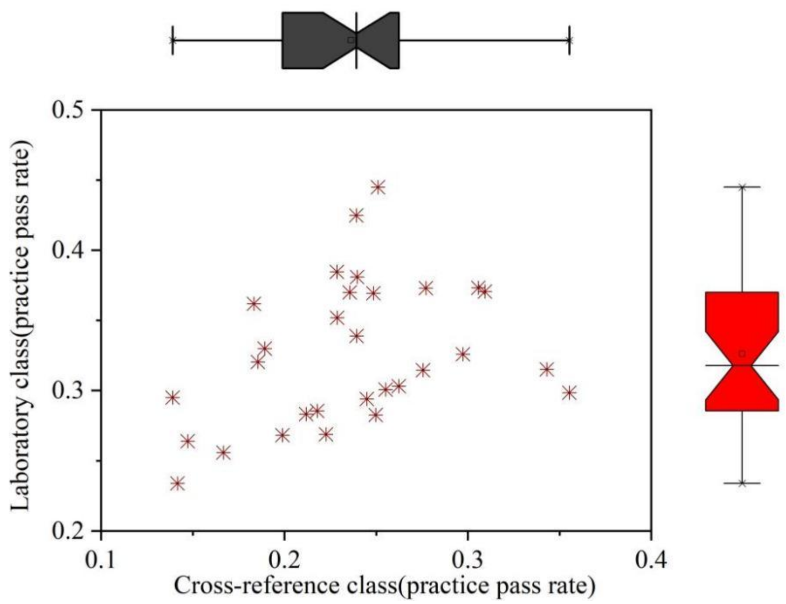
3.4. Efficiency of students in doing problems

In this section, controlled experiments are designed to verify the impact of deep learning recommendation models on learners' learning efficiency in a real online assessment platform. This section uses the learning data of the same volunteers under different knowledge points for comparison. Specifically for the 10 subjects summoned first deep learning model recommendation scenarios under the doing data, recorded as the experimental group, and then collect no recommendation scenarios under the doing data, recorded as the control group. The data collected from the two groups were analyzed to determine the volunteers' mastery of the learned knowledge points, and then to determine the impact of the presence or absence of recommendations on the learning effect. The effectiveness of the recommendation model in real-world scenarios is compared by collecting practice question data and test data from the experimental and control groups. The collected data of the experimental and control groups are shown in Table 5.

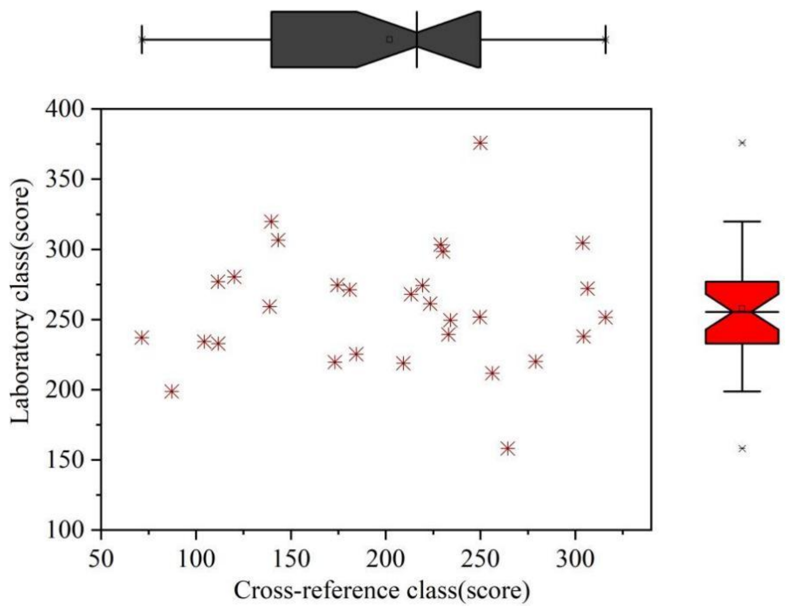
Table 5. Experimental data of the experimental group and the control group

Number	Laboratory class		Cross-reference class	
	Number of times/submission times (pass rate)	**Test score**	**Number of times/submission times (pass rate)**	**Test score**
1	32%	300	37.6%	300
2	33.2%	264	31.2%	294
3	17.54%	135	26.74%	215
4	18.2%	238	30%	218
5	26.12%	189	35.9%	232
6	21.9%	253	30.7%	300
7	20.72%	112	26.42%	176
8	25.3%	234	31.96%	274
9	27.64%	236	35%	286
10	17.64%	184	32.54%	237

A paired-samples t-test of the data is shown in Figure 2, which shows that the mean test scores of the experimental group are higher than those of the control group (253.2>214.5), indicating that the volunteers are better able to master the learned knowledge points in the scenarios with recommendations. At 95% confidence interval, P=0.0045<0.05, indicating that there is a significant difference in the test scores of the volunteers' mastery of the knowledge points with and without the recommended scenarios, and this difference is statistically significant. It can also be seen that for the control group, the volunteers' submission pass rate during practice is lower than that of the experimental group (24%<31.8%), P=0.0036<0.05, indicating that there is a significant difference in the submission pass rate of volunteers' usual practice with or without the recommended scenarios, and this difference is statistically significant. The reason for analyzing the low pass rate in the control group is that because the practice questions are subjective for volunteers to find, sometimes they may choose harder questions or questions that don't match with the current learning points, which is beyond the volunteers' own knowledge level, resulting in the submission can't be passed. In the experimental group, the practice questions are recommended by the deep learning model, which takes into account the current knowledge level of the volunteers and saves the volunteers' time to search for the next question among a large number of questions, thus improving the passing rate and the efficiency of doing the questions.



(a) Practice pass rate



(b) Score

Figure 2. The experimental group and the control group data pair sample T test

4. Conclusion

In order to better respond to the development of the information age, this paper designs a personalized recommendation system for English teaching resources based on deep learning, and proposes a personalized English teaching mode, so that the way of learning knowledge also becomes richer and multilevel. This study mainly adopts survey method and experimental research method to comprehensively explore the effectiveness and reliability of personalized teaching mode.

After the study, we found that the personalized teaching mode using deep learning can effectively promote students' English test scores, independent learning ability, critical thinking, innovative thinking, etc., which is a significant advantage compared with the traditional classroom teaching methods. In the deep learning recommended scenario, there is a significant difference between the test scores of the experimental group and the control group in terms of mastery of knowledge points (P=0.0045).

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