

Research Article

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Research on the construction and reform path of online and offline mixed English teaching model in the internet era

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Abstract: The Internet era resulted in the rise and advancement of MOOK, WeChat, and mobile networks, making it possible to expand English teaching methods. However, the English teaching industry has the problem of not valuing students' personalized cognition, and the accuracy of teaching resource delivery is low. Therefore, the research uses the noise gate analysis method to design a cognitive diagnostic model for students and designs an English teaching resource recommendation model in view of a convolutional joint probability matrix (JPM) decomposition algorithm. The research results showed that the cognitive diagnostic model designed in the study had a higher accuracy. Compared to traditional algorithms, the overall recommendation effect of the English teaching resource recommendation model had an average improvement of 11.63% and compared to the JPM algorithm combined with cognitive diagnosis (CD), the overall recommendation effect value had an average improvement of 1.977%. When recommending complex teaching resources, the recommendation effect value had an average improvement of 11.54% compared to traditional algorithms, and the overall average improvement was 1.877% compared to the JPM algorithm combined with CD. In the experimental group, with the assistance of the research algorithm, students' grades improved by an average of 2.38 points, which was significantly higher than the 0.89 points in the control group. The experiment showcases that the CD and recommendation model designed by the research has higher accuracy, can help improve the efficiency of teaching resource recommendation, reduces teaching costs, and has certain application value.

Keywords: mixed education mode, English teaching, convolutional neural network, matrix decomposition, recommended teaching resources

1 Introduction

The rapid development of Internet technology marks our entry into a brand-new information age, one of the most notable features of which is the massive growth of data and information. In this era, countless data are generated and circulated on the Internet every day from a variety of sources, including text, images, videos, and interactive exchanges. This massive amount of data have not only changed people's way of life but also profoundly affected the field of education, especially English language teaching (ET) [1]. ET has received the influence of network technology in both vocabulary and grammar, and the online and offline mixed (OOM) ET model has been widely promoted [2,3]. The educational reform in the Internet era (IE) is to combine Internet technology with ET, reform traditional ET models with the help of multi-media teaching means and digital teaching resources (TR), and form a new ET model that adapts to the development of the IE, to improve ET efficiency [4]. However, as far as international education is concerned, ET has not received enough attention,

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let alone adequate research [5]. Therefore, the aim of this study is to explore and analyze how to innovate and improve the methods and models of ET and learning in such a data-rich environment. The study focuses on building an English OOM teaching model adapted to IE and explores the possibility of combining cognitive diagnosis (CD) and TR recommendation models with Internet technologies. It is hoped that this research will not only improve the teaching effectiveness but also students' learning efficiency and provide new perspectives and methods for modern English teaching.

2 Related works

In the IE, combining OOM ET with network technology is one of the hot topics studied by scholars. Chowdhury T I proposed a special comparative analysis method to analyze data and design a model of English education. They used a snowball random sampling method to collect data, determine online English education satisfaction, construct a topological structure that perceives the level of online ET, and evaluate the research structure for internal consistency. The research indicated that the data analysis model constructed by the research accurately perceived students' wishes and enhanced the ET [6]. Huang Y and his team members designed a web-based online ET platform. They used the Internet to design the platform's hardware and software, used the mean clustering method to cluster learner data on the network, and combined collaborative filtering (CF) algorithms to suggest relevant courses for users. The test indicated that the platform designed by the research had high security, high satisfaction, and fast response [7]. Wang J and other scholars designed a higher education English digital resource library through cloud platform technology and conducted research and analysis on system requirements according to the requirements analysis steps to ensure resource collection and storage. Resource integration and management were achieved through virtualization and distributed storage technology. The simulation results showed that the resource library designed by the research was conducive to achieving resource sharing among multiple platforms and enhancing the utilization rate of English teaching resources (ETR) [8]. Chen W designed a dynamic student English data management system using artificial intelligence computer vision technology, enabling AI archiving and dynamic user access, generating dynamic data processes, managing student data, and comparing it with existing solutions. The simulation results showed that the dynamic student data management system reduced the probability of data loss, had good operational efficiency and reliability, and improved the efficiency of data management in English education [9]. Tang Y and other scholars designed a parallel intelligent artificial education system to collect students' movement data during English learning and evaluate learning conceptual knowledge through neighborhood classification. It also provided feedback during the learning process, thereby providing students with adaptive instructions and personalized learning services, helping them complete the learning process, and improving learning efficiency [10].

As an important regression analysis method, matrix decomposition is widely used in various model construction. For enhancing the data representation learning tasks, scholars like Sun Y proposed an adaptive graph regularized non-negative matrix (NNM) factorization method based on global constraints, which utilized the self-representation characteristics of data to encode the data representation's related structure. Combined with the graph decomposition technology, it reduced computational complexity, improved data discrimination and convergence effects, reduced computational model complexity, and improved computational efficiency [11]. To fully characterize heterogeneous network clusters, Zhang B and other scholars presented a joint learning model in view of graph embedding and NNM decomposition. Using graph embedding and potential network structures to simultaneously extract and cluster features, the clustering problem was changed into a constraint optimization problem, and an objective function solution was constructed. Experimental results showed that the joint learning model reduced computational time, accurately revealed structural-functional characteristics, and had good operational efficiency [12]. To improve the accuracy of community structure detection, scholars such as Chang Z proposed a community structure detection algorithm based on NNM factorization, which compared the clustering quality of synthetic networks with real-world networks, analyzed the topology and functions of complex networks, and approximated the maximization of network

modules. The experiment illustrated that the improved algorithm reduced network analysis and calculation costs and improved the accuracy of community structure detection [13]. To solve the problem that the maximum margin matrix decomposition is biased towards small sample size analysis, Ravakhah M proposed a hierarchical maximum margin matrix decomposition analysis method, which performed regression analysis based on non-overlapping threshold training data and used an unbalanced tree for rating estimation. The experiment illustrated that the improved analysis method had faster training and testing speed and higher accuracy than traditional analysis methods [14]. To solve the problem of learning feature redundancy in multi-view clustering methods, Cui et al. presented a manifold learning NNM decomposition method based on non-redundant regularization. By minimizing the defined non-redundant regularization factor, using the data manifold structure information manifold regularization factor, analyzing the characteristics of different views, and combining iterative optimization strategies, the redundant information between multiple views was ultimately reduced [15].

Although the above studies have achieved some results in the field of OOM ET, there are still some limitations in data processing and recommendation of TR in the current studies. Moradi and Sharifi's approach, although capable of constructing a topology that senses the level of online ET, may suffer from inefficiency in dealing with large-scale and complex learning data [16]. Similarly, although Esmaeili et al.'s online ET platform performed well in terms of user experience, there is still room for improvement in accurately recommending personalized TR [17]. Nejad et al.'s digital repository of English in colleges and universities made progress in terms of resource sharing; however, it did not provide adequate solutions in terms of personalized recommendation of resources and assessment of learning effects [18]. In summary, many scholars have attempted to improve students' English learning efficiency by combining Internet technology. However, with the boost of IE, more extensive and in-depth research is needed to help reform traditional ET models. Therefore, this study uses deterministic input and noise gate models based on time sensitivity to conduct CD for students, Recommending ETR based on the convolutional joint probability matrix (JPM) decomposition model (DM) is expected to help improve learning efficiency and improve the OOM ET model.

3 Construction of OOM English teaching model

3.1 Student CD based on time-sensitive deterministic input, noise, and gate (TDING) model

To reform the OOM ET model, it is first necessary to construct an accurate algorithm model to conduct CD for students, understand their mastery of knowledge points (KP), and make personalized resource recommendations. The most widely used cognitive diagnostic model in research is the latent classification model [19,20]. However, the hidden impact factors in the potential classification model are not overall. Hence, this study is based on relevant psychological diagnostic techniques, combined with students' previous KP, and based on potential classification models, presented a TDING model. Figure 1 indicates the algorithm of the TDING model.

The TDING model assumes that the target student is u_i , and filters redundant data with smaller relationships in view of the basic information of student u_i for getting the initial student set $US = \{u_1, u_2, u_3, \dots, u_m\}$, test question (TQ) set $TS = \{t_1, t_2, t_3, \dots, t_n\}$, and KP set $KS = \{k_1, k_2, k_3, \dots, k_l\}$. After that, the students related data in the system is used to construct a related matrix and record it as $R_{m \times n}$, as shown in formula (1).

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} & \cdots & r_{1n} \\ r_{21} & r_{22} & r_{23} & \cdots & r_{2n} \\ r_{31} & r_{32} & r_{33} & \cdots & r_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & r_{m3} & \cdots & r_{mn} \end{bmatrix}. \quad (1)$$

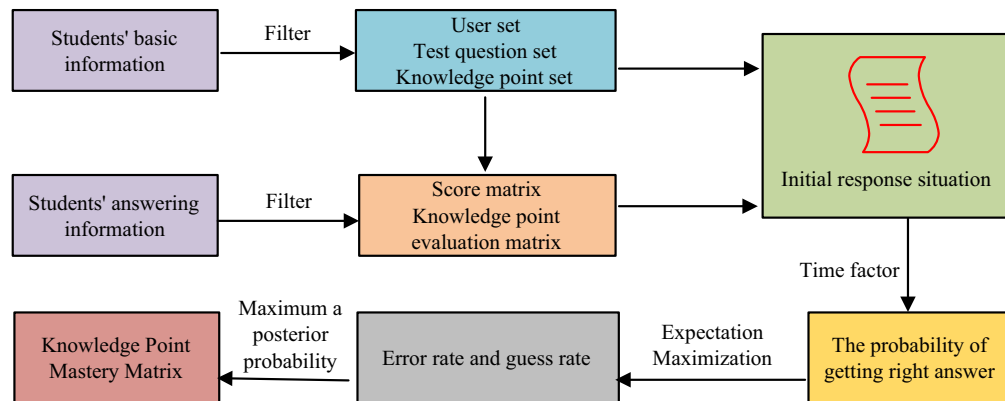


Figure 1: TDING model algorithm flowchart.

The KP inspection matrix is constructed by using the KP data labeled by some discipline experts from universities and colleges. The matrix is marked as $Q_{n \times l}$, and the matrix Q is shown in formula (2).

$$Q = \begin{bmatrix} q_{11} & q_{12} & q_{13} & \cdots & q_{1l} \\ q_{21} & q_{22} & q_{23} & \cdots & q_{2l} \\ q_{31} & q_{32} & q_{33} & \cdots & q_{3l} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ q_{n1} & q_{n2} & q_{n3} & \cdots & q_{nl} \end{bmatrix}. \quad (2)$$

Then, each student u_i could get a KP mastery vector (MV), $\vec{a}_i = \{a_{i1}, a_{i2}, a_{i3}, \dots, a_{il}\}$ is set, where $a_{ij} = 1$ indicates that student u_i has KP k_j , and $a_{ij} = 0$ showcases that student does not have KP k_j . The TDING model ultimately is for obtaining the student KP mastery matrix $A = \{\vec{a}_1, \vec{a}_2, \vec{a}_3, \dots, \vec{a}_m\}$, and the initial response situation of the students is defined as shown in formula (3).

$$\xi_{ij} = \prod_{k=1}^l a_{ik}^{q_{jk}}. \quad (3)$$

where $\xi_{ij} = 1$ illustrates that student u_i has mastered well all the KP examined by TQ t_j , whereas $\xi_{ij} = 0$ indicates that the student u_i did not master all the KP examined by TQ t_j . In the learning process, students may make certain mistakes and guesses when answering questions. Therefore, the definition of error rate (ER) and guess rate (GR) is shown in formula (4).

$$\begin{cases} s_j = p(r_{ij} = 0 | \xi_{ij} = 1) \\ g_j = p(r_{ij} = 1 | \xi_{ij} = 0) \end{cases}. \quad (4)$$

where p denotes the probability, s is the ER, and g is the GR. Combining the related formula and matrix, the positive response rate $p(r_{ij} = 1 | a_i)$ is calculated using the formula shown in formula (5).

$$p(r_{ij} = 1 | a_i) = (1 - s_j)^{\xi_{ij}} g_j^{1 - \xi_{ij}}. \quad (5)$$

The personalized information of students will affect the positive response rate. Combining formula (5) for obtaining the final positive response rate of students is shown in formula (6).

$$p(r_{ij} = 1 | a_i) = T(\lambda, \alpha, \beta)(1 - s_j)^{\xi_{ij}} g_j^{1 - \xi_{ij}} = \frac{\sum \beta(1 - \lambda t^\alpha)}{\text{count}(\beta)(1 - s_j)^{\xi_{ij}} g_j^{1 - \xi_{ij}}}. \quad (6)$$

where λ and α serve as constant parameters, parameter β serves as the case of students answering questions t_j in history, and parameter T is a time parameter. The TDING model in this study considers that students have a forgetting effect on questions answered in history, and the times they answer questions have a consolidation

memory effect. At the same time, both of these effects belong to a function of time. Therefore, the study brings a factor for enhancing the model. If the student answers correctly, the value is 1, otherwise, the value is 0, indicating the times the student answers the TQ. By maximizing the edge likelihood in the formula, obtain the maximum likelihood estimator (MLE) of the gain/loss ER \bar{s}_j and the MLE of the GR \bar{g}_j , and ultimately obtain the student's KP MV estimator \bar{a}_i . Due to the existence of multiple hidden variables in the TDING model that cannot be directly observed, it is essential to address the parameter estimation for incomplete data. The TDING model is a conditional distribution \bar{a}_i of response data given a student's KP MV r_{ij} . Here it is assumed that the student's response to each question is independent given the attribute vector, so the conditional distribution of \vec{r}_i is shown in formula (7).

$$L(\vec{r}_i | \alpha_i) = \prod_{j=1}^n p'(r_{ij} = 1 | \vec{\alpha}_i)^{r_{ij}} (1 - p'(r_{ij} = 1 | \vec{\alpha}_i))^{1-r_{ij}}. \quad (7)$$

where L is a likelihood function, and the conditional probability distribution of the score matrix R for m students U can be obtained as shown in formula (8).

$$L(R | A) = \prod_{i=1}^m L(\vec{r}_i | \alpha_i) = \prod_{i=1}^m \prod_{j=1}^n p'(r_{ij} = 1 | \vec{\alpha}_i)^{r_{ij}} (1 - p'(r_{ij} = 1 | \vec{\alpha}_i))^{1-r_{ij}}. \quad (8)$$

where A is the KP mastery matrix. To calculate the estimators of guess factors and error factors, the total likelihood function of the response data is given as shown in formula (9).

$$L(R) = \prod_{i=1}^m L(\vec{r}_i) = \prod_{i=1}^m \prod_{j=1}^{2^k} p((\vec{r}_i | \vec{\alpha}_j)) p(\vec{\alpha}_j). \quad (9)$$

The MLE of ER and GR obtained by combining the maximum expectation algorithm is shown in formula (10).

$$\bar{s}_j = \frac{I_{jk}^{(1)} - R_{jk}^{(1)}}{I_{jk}^{(1)}}, \quad \bar{g}_j = \frac{R_{jk}^{(0)}}{I_{jk}^{(0)}}. \quad (10)$$

where $I_{jk}^{(0)}$ represents the expected number of students who fully master all the KP examined in the first TQ, and is the expected number of students in the k KP mastery mode. $R_{jk}^{(0)}$ represents the expected number of students who correctly answer the j TQ in $I_{jk}^{(0)}$. The meanings of $I_{jk}^{(1)}$ and $R_{jk}^{(1)}$ are similar to those of $R_{jk}^{(0)}$ and $I_{jk}^{(0)}$, except that $I_{jk}^{(1)}$ and $R_{jk}^{(1)}$ are the values obtained when the students master all the KP tested in the first TQ. Therefore, the values of $I_{jk}^{(0)}$, $R_{jk}^{(0)}$, $I_{jk}^{(1)}$, and $R_{jk}^{(1)}$ can be calculated from the estimates, and new estimates of ER s_j and GR g_j can be obtained. The calculation is repeated until each component converges. The MLE of the loss ER and the MLE of the GR are found. Finally, the formula is combined with the maximum posterior probability algorithm to obtain the student's KP MV estimator, followed by obtaining the student's KP mastery matrix A . This process leads to the completion of the diagnosis of the student's cognitive ability level.

3.2 Recommendation of TR based on the CUMF model

The research combines intelligent algorithms to personalized recommend ETR for students based on the student CD, improving teaching effectiveness, and promoting the reform of OOM ET models. The study combines a Convolutional Neural Network (CNN) with a cognitive diagnostic model built based on TDING to propose a TR recommendation method in view of the Convolutional Unified Probability Matrix Factorization (CUMF) model. Based on multi-layer deep neural networks, CNN has introduced a more effective feature learning component, making it more capable of feature learning. Specifically, it has introduced local displacement-connected convolutional layers and pooling layers before the original fully connected layer [21,22]. The overall hierarchical structure of CNN is shown in Figure 2.

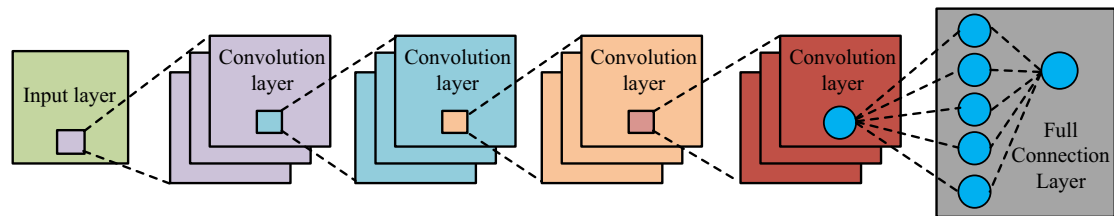


Figure 2: Overall hierarchical structure of CNNs.

The main function of CNN is to reveal the potential features of ETR, obtain implicit feature vectors (IFV) for English tests, and construct implicit feature matrix (IFM) representations of tests with CNN weight parameters for training in JPM DM. The CUMF model combined with the convolutional network is shown in Figure 3.

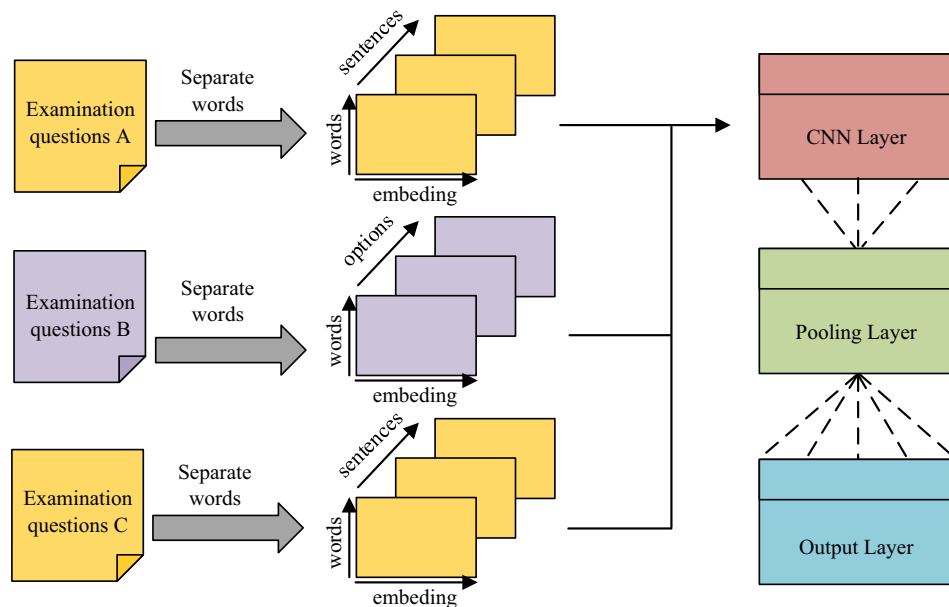


Figure 3: CNN-CUMF model diagram.

CUMF combines factors such as students' past answers, knowledge levels, mastery of English test sites, and forgetting effects. Meanwhile, it uses CNN to mine ETR, and through non-linear transformation by CNN, it is incorporated into a JPM DM for forecasting student performance. Finally, combined with the related matrix obtained from the TDING model, personalized ETR is recommended to improve students' learning efficiency and ultimately improve teaching effectiveness. The CUMF recommendation algorithm is shown in Figure 4.

The CUMF recommendation algorithm framework first filters out exam information based on English students' response records and then divides the related information into English word sets through word segmentation. Then, the word is transformed into a word vector (WV) through word embedding technology, and the English WV is used as the input of the CNN. Certain transformations related layers obtain the implicit matrix (IM) of the test with CNN and use the IM of the test as the IM parameter in the JPM DM. Last, through the KP mastery matrix from the TDING model, the test KP correlation matrix from specialists, and the test score matrix (TSM) based on the student exam situation, a random gradient descent algorithm is used to obtain each matrix, and these implicit feature matrices are used to obtain the TSM. The implicit matrices' dot product operation is used to predict students' performance in testing ETR. Finally, based on students' cognitive

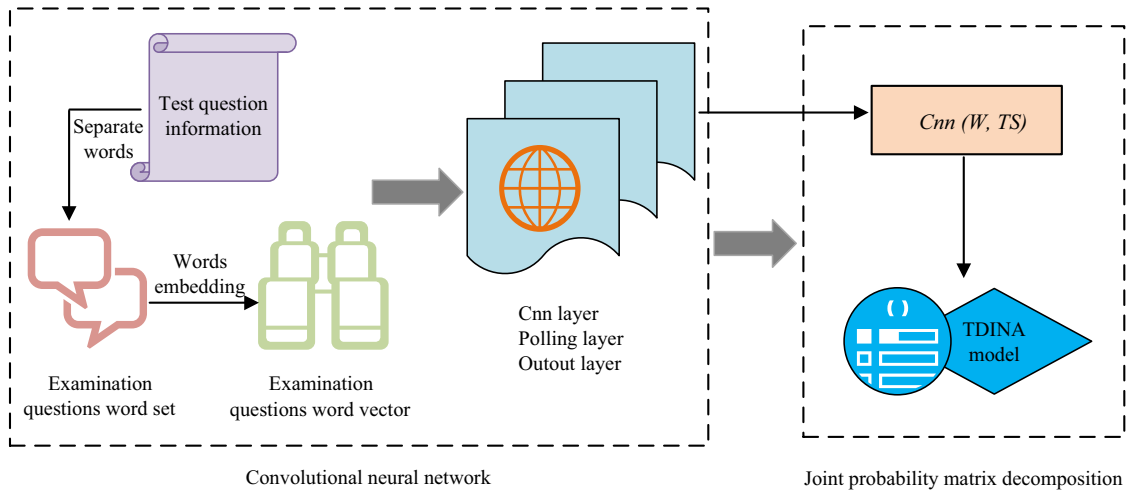


Figure 4: CUMF recommendation algorithm framework.

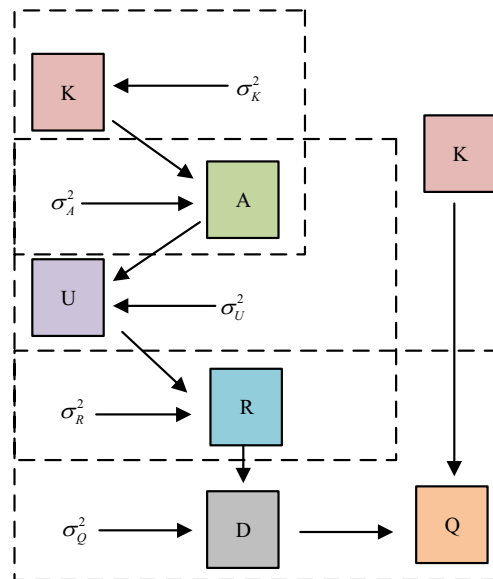


Figure 5: Convolutional JPM DM.

abilities, whether to recommend video TR is chosen. This study combines CNN with a JPM DM, and presents a DM for convolutional joint probability matrices, as shown in Figure 5.

The prior probabilities of initializing implicit feature matrices U and K follow a Gaussian distribution (GD) with a mean value of 0 and a variance of σ^2 , and the weight probability distribution of convolutional network neurons is shown in formula (11).

$$\begin{cases} p(U|\sigma_U^2) = \prod_{i=1}^m G(U_i|0, \sigma_U^2 I) \\ p(K|\sigma_K^2) = \prod_{i=1}^m G(K_i|0, \sigma_K^2 I) \\ p(W|\sigma_W^2) = \prod_k G(W_k|0, \sigma_W^2) \end{cases} \quad (11)$$

where G is a prior probability, U and K are IFM, and W serves as the weight of the convolutional neural network. The probability distribution of the IFV D_j from the CNN and the IFM D for Test j is shown in formula (12).

$$\begin{cases} D_j = \text{Cnn}(W, T_j) + \varepsilon_j \\ p(D|W, T, \sigma_D^2) = \prod_{j=1}^n G(D_j | \text{Cnn}(W, T_j), \sigma_D^2 I). \end{cases} \quad (12)$$

where T_j is the WV of the TQ generated by word embedding technology, and ε_j is the Gaussian noise. The implicit vector (IV) U_i of student i and the IV D_j of the TQ j illustrate that the scoring probability r_{ij} of student i on the TQ is respectively distributed and independent of a GD with a mean value of h and a variance of σ_A^2 . The related mathematical expression is shown in formula (13).

$$p(R|U, D, \sigma_R^2) = \prod_{i=1}^m \prod_{j=1}^n [G(r_{ij} | h(U_i^T \text{Cnn}(W, T_j)), \sigma_R^2 I)]^{I_{ij}^R}. \quad (13)$$

where I_{ij}^R serves as an indicator function (IF). If student i has done KP j , then $I_{ij}^R = 1$. Or else, $I_{ij}^R = 0$ and $h(x)$ are sigmoid functions, that is, the value of $U_i^T \text{Cnn}(W, T_j)$ is mapped to the range of $(0, 1)$. Similarly, the IFV U_i of student i and the IFV K_j of KP j , showcase that the grasping α_{ij} of KP j by student i satisfies a GD with an average value of $h(U_i^T K_j)$ and a variance of σ_A^2 . The related expression for a conditional probability distribution is shown in formula (14).

$$p(A|U, D, \sigma_A^2) = \prod_{i=1}^m \prod_{j=1}^l [G(\alpha_{ij} | h(U_i^T K_j), \sigma_A^2 I)]^{I_{ij}^A}. \quad (14)$$

where I_{ij}^A serves as an IF. If student i grasped KP j , then $I_{ij}^A = 1$, if not, then $I_{ij}^A = 0$. Similarly, the IFV v of TQ i and the IFV K_j of KP j indicate that the association between TQ i and KP j meets a GD with a mean value of $h(\text{Cnn}(W, T_j)^T K_j)$ and a variance of σ_Q^2 . The related distribution is shown in formula (15).

$$p(Q|D, K, \sigma_Q^2) = \prod_{i=1}^m \prod_{j=1}^l [G(\alpha_{ij} | h(\text{Cnn}(W, T_j)^T K_j), \sigma_Q^2 I)]^{I_{ij}^Q}. \quad (15)$$

where I_{ij}^Q serves as an IF. If TQ i examines KP j , then $I_{ij}^Q = 1$, or else $I_{ij}^Q = 0$. Combining the above prior probability distribution formula, a posterior probability distribution of the matrix can be obtained, and then the implicit characteristic matrix (ICM) for students, the ICM for TQ, and the ICM for KP can be obtained to further obtain the variance parameter $\varphi_A = \frac{\sigma_R^2}{\sigma_A^2}$ of the correlation matrix for students' mastery of KP and the variance parameter $\varphi_Q = \frac{\sigma_R^2}{\sigma_Q^2}$ of the correlation matrix for KP annotated by experts. Then, by multiplying the IFM of the student and the IFM of the TQ, the student's score is inferred. Finally, based on this score and students' grasping of KP, personalized TR can be recommended for students.

4 Online and offline English learning model simulation test

4.1 Analysis of students' cognitive diagnostic efficiency

To ensure the effectiveness of OOM ET models and verify the TDING model's effectiveness proposed in the study in students' CD, a comparative experiment was conducted between TDING and classical CD methods. Since the test results of different hardware devices may have large differences, the study was conducted in the same experimental environment, which is shown in Table 1.

The study utilized the publicly available dataset English Language Learner Corpus (ELLC). This dataset is provided by the International Agency for the Teaching of English as a Foreign Language and contains learning data from English learners from different countries and at different stages of learning. The ELLC dataset

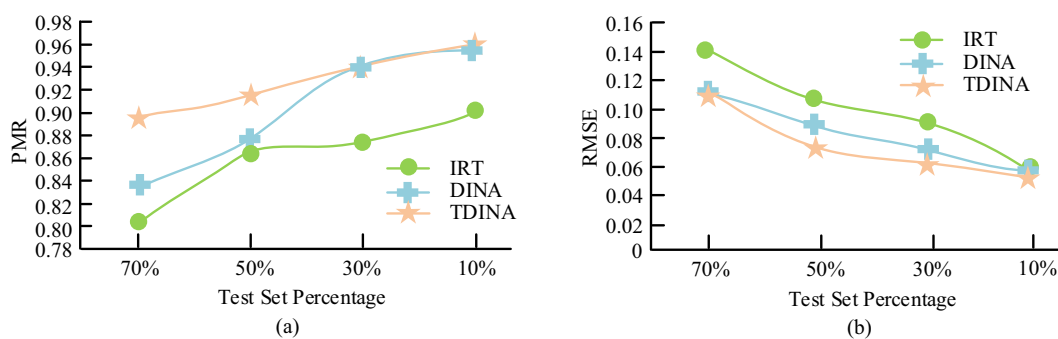
Table 1: Experimental environment information

Name	Configuration
Video card	GTX 1080 Ti
CPU	Inter(R)Core(TM)i5-7200U
GPU-accelerated library	CUDA 10.0
Memory	64 GB
Operating system	Windows 10
Platform	MATLAB R2014a

contains the learning data of more than 10,000 students at different levels of proficiency, ranging from basic to advanced. The data are not only rich in content but also highly diverse and representative because learners come from different countries and cultural backgrounds. The comparative objects include Item Response Theory and Deterministic Inputs, Noise, and Gate (DINA) models. During the experiment, 10, 30, 50, and 70% of the datasets were chosen as test datasets, and commonly utilized evaluation criteria in the industry, namely, Pattern Match Rate (PMR) and Root Mean Square Error (RMSE) indicators, were utilized to detect the modeling effects. PMR is a measure of the predictive accuracy of a model. It evaluates the performance of a model by comparing the similarity between the output patterns predicted by the model and the actual observed data patterns. The higher the PMR value, the better the predictive ability of the model. In cognitive diagnostic models, PMR can effectively reflect the accuracy of the model's judgment of the learner's ability level and knowledge mastery and is a key indicator for assessing the effectiveness of the model in actual teaching applications. RMSE is a measure of prediction error. It calculates the square root of the average of the squared values of the differences between the predicted and actual values. The lower the RMSE, the higher the predictive accuracy of the model. The RMSE can visualize the differences between the model predictions and the actual data, which helps to evaluate the accuracy and reliability of the model in detail. The experimental results of different cognitive diagnostic model values under the proportions of each test dataset are shown in Figure 6.

In Figure 6, when modeling students for CD, the PMR value of the TDING model as a whole has increased by 4.664% compared to the other two classical modeling methods, while the RMSE value has decreased by 1.412% compared to the other two modeling methods. The above results indicated that the TDING method significantly enhanced the CD and the diagnostic modeling. To further verify the reliability of the cognitive diagnostic model for students in OOM ET, the study used the Receiver Operation Characteristic Curve (ROC) for estimating the function of the cognitive diagnostic model, as shown in Figure 7.

The ROC curve is a graphical presentation of the performance of a classification model, which evaluates the model's classification ability by comparing the True Positive Rate and the False Positive Rate. In the field of CD, the ROC curve helps to determine the efficacy of the model in distinguishing between different cognitive states (e.g., mastery vs non-mastery), and is an important tool for evaluating the diagnostic accuracy of the

**Figure 6:** Experimental results of cognitive diagnostic model values. (a) PMR values for each model. (b) RMSE values for each model.

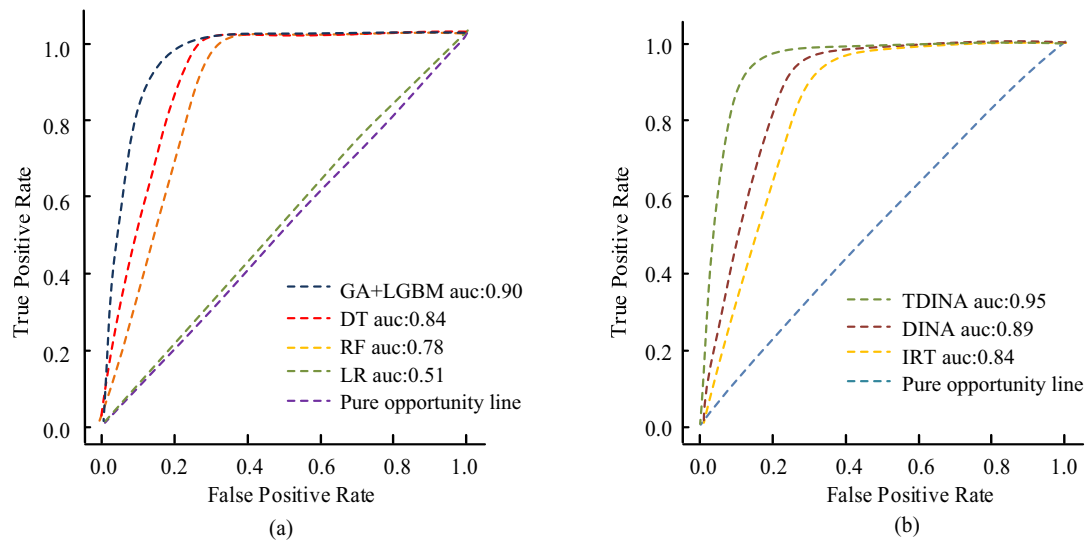


Figure 7: Performance evaluation of cognitive diagnostic models by ROC. (a) ROC curves of course selection probabilities. (b) ROC curves of different algorithms.

model. Figure 7 showcases that compared to the feature selection method of genetic algorithm combined with a light gradient boosting machine, the TDING model has the highest authenticity and can more realistically reflect the actual process of students' answering questions, thereby improving the accuracy of the cognitive diagnostic model.

4.2 Quality analysis of ETR

To verify the reliability of OOM ET models, the study used multiple public datasets for testing the research recommendation algorithm. Table 2 showcases each dataset.

During the experiment, to conclude the impact of the sparsity on different algorithms, 70, 50, 30, and 10% of all datasets were chosen as test datasets, and the remaining datasets were selected as training datasets. Moreover, this study separated TR into two resources, which are simple and complex based on a difficulty value of 0.6, and conducted a comparison of the recommended effects of various TR. The related effects ($F1$ value) are illustrated in Figure 8.

The $F1$ value is the reconciled average of Precision and Recall, which is a comprehensive measure of the accuracy of the model. The $F1$ value takes into account the precision and comprehensiveness of the model and is suitable for the case of the unbalanced dataset. In recommender systems, the $F1$ value can balance the precision and recall and provide a comprehensive evaluation of the model recommendation effect, especially suitable for evaluating the effectiveness of the TR recommender system. In Figure 8, when students mastered the variance parameter $\phi_A = 0.5$ of the KP correlation matrix, the $F1$ value reached the peak, and the recommendation effect was the best. However, when $\phi_A > 0.5$, the $F1$ value gradually decreased, which meant that

Table 2: Description statistics for the dataset

Dataset	TR	Number of students	KP
English0	5,684	327	68
FrcSub	20	4,210	12
English1	20	3,912	15
English2	20	537	9

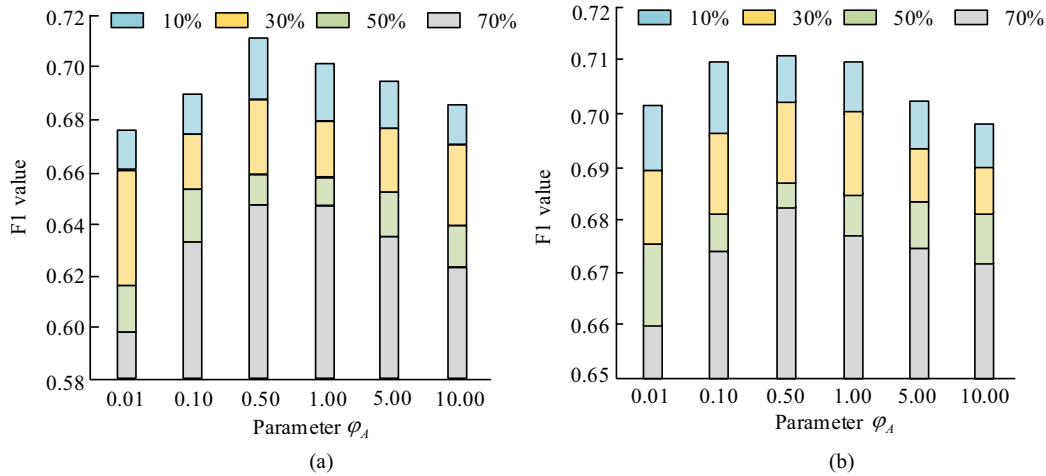


Figure 8: Effect of the first parameter on F1 value. (a) The effect of parameter φ_A on simple resource. (b) The effect of parameter φ_A on complex resource.

the recommended effect of the CUMF model gradually decreased. The variance parameters φ_Q and their related impact (F1 value) are indicated in Figure 9.

In Figure 9, the solid line serves as the impact of parameter φ_Q on the recommendation performance of complex TR models, while the dashed line serves as the impact of parameter φ_Q on the recommendation performance of simple TR models. When experts labeled the variance parameter $\varphi_Q = 1$ of the KP correlation matrix, the F1 value achieved a peak. When $\varphi_Q > 1$, the F1 value gradually diminished, which meant that the CUMF model's effect started to gradually diminish. In summary, the proportion of the test dataset and the difficulty of TR did not affect the results. The F1 value of the CUMF model first grew and diminished as the variance parameters φ_A and φ_Q gradually increased. In the CUMF model, when the study set other parameters to 0.001, φ_A to 0.5, φ_Q to 1, and related dimension to 10, the recommended effect was optimal.

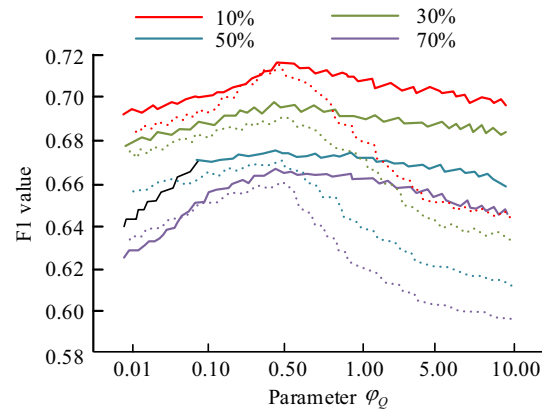


Figure 9: Effect of the second parameter on F1 value.

4.3 Effect analysis of online and offline English teaching resource recommendation

To analyze the OOM-ET model constructed through research and verify the effectiveness of English resource recommendation, this study recommended three sets of simple teaching resources (STRs) and three sets of

complex teaching resources (CTRs) to students in a simulation experiment and compared the CUMF model method with other methods, including user-based CF recommendation method. Also includes considering the deterministic input noise of CD and the gate model (DINA) approach, combined with CD's (PMF-CD) TR recommendation method, and combined with CD's JPM (QueRec) CD recommendation method. The recommended experimental results for ETR are shown in Table 3.

Table 3 indicates that when recommending STR, the $F1$ value of CUMF increased by an average of 11.63% relative to the other algorithms and increased by an average of 1.977% compared to QueRec algorithm as a whole. When recommending CTR, the $F1$ value grew by an average of 11.54% relative to the other algorithms and increased by an average of 1.877% compared to QueRec algorithm as a whole. As the test sets continued to decrease, the training sets continued to increase, the CUMF model exceeded the four algorithms in recommendation accuracy for STR and CTR. The above data indicate that the CUMF method can significantly enhance recommendation accuracy and effectiveness. The study was conducted by comparing the response time of different algorithms to compare the computational complexity. The results are shown in Figure 10.

In Figure 10, the response time of CUMF is only longer than that of DINA, with an average single response time of 0.991 s, which is shorter than that of QueRec, PMF-CD, and User-Based CF algorithms. Considering the high accuracy brought by CUMF, the study concluded that the optimized computational complexity was acceptable. For testing the effect in the actual environment, the student data were separated into two groups, G1 and G2, G1 using the algorithm proposed in the study, and G2 using traditional algorithms. A comparative experiment was conducted on the response data through a paired sample t -test. Table 4 showcases the results.

Table 4 indicates that there is a dramatic disparity in the pre-test and post-test scores in Group G1, the experimental group, while there is no dramatic disparity in the pre-test and post-test scores in Group G2, the

Table 3: Experimental $F1$ results of ETR

Recommended algorithm	Test set proportion			
	10%	30%	50%	70%
CUMF of STR	0.782	0.754	0.723	0.718
QueRec of STR	0.767	0.736	0.702	0.689
PMF-CD of STR	0.702	0.638	0.631	0.694
User-Based CF of STR	0.478	0.533	0.507	0.502
DINA of STR	0.698	0.616	0.605	0.538
CUMF of CTR	0.852	0.824	0.786	0.792
QueRec of CTR	0.831	0.796	0.788	0.758
PMF-CD of CTR	0.773	0.722	0.714	0.686
User-Based CF of CTR	0.605	0.594	0.614	0.482
DINA of CTR	0.742	0.707	0.654	0.692

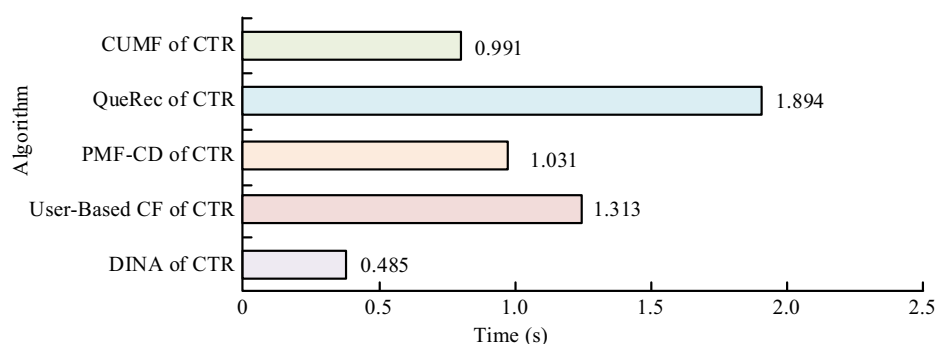


Figure 10: Comparison of computational complexity between different algorithms.

Table 4: Comparative experimental results

Answer result data	G1		G2	
	Pre-test	Post-test	Pre-test	Post-test
Number of people	30	30	30	30
Standard deviation	4.145	4.065	5.366	5.045
Mean square deviation	0.955	0.895	1.315	1.035
Average score	81.135	83.515	81.266	82.165
conspicuousness	0.12%		0.04%	
Difference significance	4.15%		6.52%	
Correlation coefficient	0.964		0.765	
t	-2.095		-1.762	

control group. In view of the *t*-test data results of G1 and G2 groups in Table 4, it showcased that the overall learning effect of G1 group students who use the TR recommended by the CUMF model-based TR recommendation algorithm elaborated by the research institute for autonomous learning is better than that of the control group, namely, G2 group students who only learn through independent search and browsing. Therefore, the effectiveness and feasibility of the proposed TR recommendation algorithm in view of the CUMF model applied in OOM English education models have been confirmed.

5 Discussion

At a time when Internet technology is developing rapidly, the field of education is undergoing a profound change. Especially in the field of ET, the rise of the OOM ET model marks the effective integration of traditional teaching methods and modern technology [23]. This model not only reflects the current development trend of educational technology but also the need for personalization and flexibility in modern education. For English teaching, the development and study of this model have important theoretical and practical value. However, due to the relative newness of this field, research on the OOM ET model in the existing literature is still relatively limited. Most of the existing studies focus on the evaluation of the effectiveness of online teaching, while there are fewer studies on the online-offline combined teaching model [24]. The aim of this study was to fill this gap by providing a comprehensive perspective to understand and improve modern English language teaching through an in-depth analysis of OOM teaching models. The study first validates the effectiveness of using the TDING model in CD, which echoes the research of Sharifi et al. who also found that incorporating technological tools can significantly improve the quality of teaching and learning. However, unlike the study by Sharifi et al., this study went a step further by integrating multiple data analysis tools, such as PMR and RMSE, and validated its effectiveness on real-world datasets [25,26]. In addition, the OOM ET model proposed in the study demonstrated significant advantages in terms of teaching effectiveness and student engagement compared to the traditional offline teaching model. This is similar to the study by Kosari et al. who noted that the richness and interactivity of online TR are crucial for improving learning outcomes [27]. The innovation of the study is that it not only considers the use of online resources but also pays attention to the integration of offline teaching to optimize the teaching method. The results of the study have important implications for current ET practices. Compared with the study by Zamani and other scholars, the teaching model proposed by the study pays more attention to the construction of personalized learning paths, which is important for meeting students' different learning needs and optimizing the allocation of TR [28]. Although this study provides an in-depth analysis and empirical study of the OOM ET model, there are still some limitations. First, the study mainly relies on a specific dataset and experimental setting, which may not be sufficient to comprehensively reflect the effectiveness of teaching and learning in different cultural contexts, limiting the generalizability of the findings. Second, although a variety of data analysis tools and assessment metrics were used, they may not fully cover all aspects of the OOM ET model. Therefore, some of the assumptions and

conclusions of the study may need to be updated and revised in the future, given the rapid developments in technology and the field of education. The best practices of the OOM ET model may change as new technologies emerge and pedagogical concepts are further developed.

6 Conclusion

The aim of this study is to improve students' English learning outcomes by modeling CDs using the innovative TDING model and optimizing TR recommendations based on the CUMF model. The results of the study not only confirmed the advantages of the TDING model in terms of precision and accuracy but also demonstrated the significant effect of the CUMF model in improving the accuracy of teaching resource recommendations. The TDING model was overall 4.664% higher than the other two classical modeling approaches in terms of PMR value, and 1.412% lower than the other two approaches in terms of RMSE value. This significant performance improvement indicated that the TDING model had a clear advantage in understanding and predicting students' learning states. This advantage stemmed from the unique algorithm design of the TDING model, which captured and analyzed student learning data more accurately, thus providing teachers and educators with a more accurate analysis of students' cognitive states. The CUMF model demonstrated excellent performance in recommending TR. The *F1* value of the CUMF model was significantly higher than that of the other four algorithms both in recommending simple TRs and complex TRs, especially in comparison with the QueRec algorithm. This result indicates that the CUMF model has a significant advantage in increasing the ETR recommendation accuracy and improving the recommendation effect, which is attributed to its efficient algorithmic design in processing complex data and understanding user needs. Although this study has achieved remarkable results, there are some limitations. The main limitation is that there is still room for improvement in the text feature extraction efficiency of ETR. Future research could consider more advanced feature extraction methods for serialized data to improve the accuracy and learning efficiency of recommender systems. In addition, further research can explore how these models can be applied to ET in different cultural and linguistic contexts to verify their general applicability and effectiveness.

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