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Article

Research on Intelligent Planning of the Path to Improve Intercultural Communication Competence of Business English in Colleges and Universities Driven by Big Data

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Abstract: Aiming at the limitations of the traditional teaching mode and the failure of big data technology to realize the deep integration with the whole process of teaching, the study proposes a cross-cultural communication integration teaching mode based on personalized teaching resources recommendation algorithm. The personalized teaching resource recommendation model proposed in this paper is a personalized teaching resource recommendation method based on cognitive diagnosis and collaborative filtering, MNCD-NMF, which combines multi-factor neurocognitive diagnosis and neural matrix decomposition model to model students' knowledge mastery and obtain students' personalized learning characteristics. Then, the personalized learning characteristics are integrated into the neural collaborative filtering model to predict the students' responses. Finally, a list of recommended learning resources was provided to students by setting different difficulty parameter ranges. Experimental and control classes were designed for teaching practice. The mean values of the four dimensions of intercultural communication competence in the experimental class were 3.45, 3.37, 3.19, 3.23 for the knowledge, awareness and behavior dimensions respectively, and 2.25, 2.29, 2.20, 2.27 for the control class, respectively, and the cross-cultural communication integration teaching model can promote the intercultural communication competence in the knowledge, awareness, affective and behavioral dimensions.

Keywords: teaching resource recommendation; business English; intercultural communicative competence; MNCD-NMF; cognitive diagnosis; neuromatrix decomposition

1. Introduction

Under the new development pattern of double-cycle economy, China's foreign trade presents an all-round and diversified development trend, not only the economic and trade exchanges with traditional trading partners such as the United States and the European Union are continuously strengthened, but also the economic and trade exchanges with the Middle East, Latin America, Africa and other regions have also seen new development [1]. In the new trade environment, many enterprises are actively expanding foreign trade, promoting foreign economic and trade cooperation by "Internet +", cross-border e-commerce, etc., which has led to the increasing demand for business English talents. However, under the traditional education model and the concept of talent cultivation, colleges and universities pay more attention to the teaching of theoretical knowledge of business English majors, and take the English level examination and the four or six level examination as the important teaching indexes, instead of neglecting the cultivation of students' intercultural communication ability, which leads to the majority of the students are not adapted to the employing needs of enterprises [2-3]. For this reason, the issue of cultivating cross-cultural communication ability of business English majors should be studied in depth.

Under the background of economic globalization, cross-cultural communication is one of its main features. The reason for this feature is that under different economic, political and cultural environments, there are obvious differences in people's business habits, consumer psychology and business values, so that foreign activities need to take these issues into account to improve the success rate of transactions [4]. Adler and Aycan point out that in the context of increasing global interconnectedness, deep divisions in culture, wealth, ideology, class, gender and ethnicity exacerbate social divisions, which can be transformed by intercultural communication from a source of problems to an invaluable resource for promoting the success of individuals, organizations and societies [5]. Gusakova and Boichuk argue that intercultural communication is based on the interpretation of intercultural symbols as the central motivating factor. Gusakova and Boichuk believe that intercultural communication is centered on the interpretation of intercultural symbols as a central motivational factor, and that the individual parameters of linguistic personality as the main constituent of the communicative process form a picture of the linguistic world reflecting the perception of the world of people from different cultures [6]. Regarding the significance of intercultural communication competence development, Aririguzoh pointed out that improper encryption of information can easily lead to misinterpretation and misunderstanding, while culturally literate communicators can reduce communication barriers and create a good communication environment by recognizing and respecting cultural differences [7]. Sahadevan and Sumangala pointed out that language, stereotypes, nonverbal signals, emotional expressions, ethnocentrism, anxiety, uncertainty, perceptions and prejudices constitute intangible barriers to cultural integration, which affects many aspects of organizational functioning, such as employee relations, staffing, team building and negotiation, etc., and the study emphasized that the exchange of ideas based on mutual understanding, respect and trustworthiness is the cross-cultural communication Research emphasizes that idea exchange based on mutual understanding, respect and trustworthiness is the core of cross-cultural communication [8]. Carbaugh argues that the development of intercultural communicative competence views communication both as a discipline and as a culturally embedded practice, and that the two are not mutually exclusive [9].

Regarding the research on the path to enhance intercultural communication competence, Lyu suggests that the path to enhance intercultural communication competence mainly includes the systematic cultivation of cultural awareness, communication skills, empathy, and adaptability in education; and helping students break through their cultural comfort zones through experiential learning, intercultural communication programs, and inclusive courses that incorporate multiculturalism [10]. Jia and Chen proposed that the concept of interculturalism should be systematically integrated into all aspects of teaching design, teaching content, teaching activities and teaching evaluation; on this basis, they put forward the cultivation strategy of using English as a medium to comfortably cope with cultural differences, and guided students to correctly utilize the language to deal with intercultural situations, so as to effectively promote the development of intercultural education [11]. Li proposed that at the strategy level, diversified educational strategies should be constructed by integrating cultural background, promoting experience exchange, optimizing curriculum design and applying technological means; and at the method level, students' intercultural communication competence should be systematically improved by means of interactive teaching, case study, role-playing, reflection and critical thinking training [12]. Guan proposed that diverse interactive and communicative exercises should be integrated into the classroom to enhance students' confidence and motivation in using English for cross-cultural communication; integrating real contexts and cultural backgrounds into language learning resources helps students better understand and handle cross-cultural situations; at the same time, through extracurricular activities, cultural exchanges, and language immersion programs, the breadth of language learning can be expanded, and overall cross-cultural competence can be enhanced through immersive experiences [13]. Ban proposed a strategy for cultivating intercultural communicative competence in the three dimensions of knowledge, thinking and behavior, which realizes the deep integration of cultural understanding and communication practice by optimizing the teaching content and innovating the teaching methods, and helps students to effectively satisfy their communicative needs in multicultural contexts [14]. Wang's study found that digital media may bring identity challenges while broadening cultural communication channels, and a solid cultural identity is positively correlated with intercultural communication skills, so the foundation of students' cultural identity and intercultural practice skills can be strengthened through the integration of curricular reform, technological empowerment and institutional safeguards [15].

The development of Internet information and communication technology in the context of big data has developed and revolutionized educational concepts and educational methods. Regarding the impact of big data technology on cross-cultural communication competence, Ye constructed a multilingual and multi-domain English cross-cultural communication corpus by using natural language processing and data mining techniques, and revealed the key role of understanding cultural differences, direct and clear communication strategies and positive and friendly emotional attitudes in effective cross-cultural communication by analyzing high-frequency vocabulary, commonly used expressions, communication strategies, and emotional tendencies [16]. Liang constructed a big data analysis framework covering four stages of data collection, feature analysis, pattern modeling and visualization, and extracted cultural difference features such as communication styles and emotional expressions by integrating data from multiple source platforms, which provided a systematic technical path to enhance cross-cultural communicative competence in online learning environments [17]. Jiang and Tang et al. explored the cultivation path to enhance intercultural communicative competence by deeply integrating language learning with cultural education under multimodal data [18]. Ma provides personalized, contextually relevant linguistic and cultural feedback through real-time collection of multimodal data such as voice intonation, facial expressions and gestures through wearable devices and smart environments. The framework breaks through the limitations of traditional methods in real-time adaptability, non-verbal cue integration and personalized cultural training, and provides a scalable technological solution for the cultivation of intercultural communicative competence in the smart era [19].

In order to improve the intercultural communication competence of business English in colleges and universities, the MNCD-NMF personalized teaching resource recommendation method and the intercultural communication integration teaching model incorporating the method are proposed. The personalized teaching resources recommendation method realizes the diagnosis and assessment of students' knowledge level through the MNCD model, integrates the personalized learning characteristics of students into the neural matrix decomposition model, predicts the probability of students' correctly answering the test questions, and recommends suitable teaching resources for students. The teaching mode is to integrate the content recommended by the MNCD-NMF model for cultivating intercultural communicative competence into the learning process, organically combine it with the language skill objectives, content and requirements of the course, acquire intercultural knowledge and cultivate intercultural skills. By optimizing the teaching process, the effect of the intercultural communication integration teaching mode on the improvement of students' intercultural communication competence in business English is verified, aiming at deepening the application of big data technology in the teaching field and providing a replicable and popularized practice paradigm for the teaching reform of intercultural communication business English courses in colleges and universities.

2. MNCD-NMF personalized teaching resource recommendation methodology

2.1. Cognitive diagnostic techniques

Cognitive diagnostics can model students' knowledge mastery, which provides for educational recommendations, and the results diagnosed by good cognitive diagnostic models can improve recommendation accuracy. This section introduces two classic models in the field of cognitive diagnosis: item response theory and deterministic input noise and gate models.

2.1.1. Project Response Theory

The goal of item response theory is to assess students' abilities and was first widely used in the field of psychology. Later, it also achieved good results in the field of education and is a theory commonly used in cognitive diagnosis. In educational institutions, the item response theory model can be used to estimate the student's ability value θ on the knowledge point based on the student's previous work, so as to understand the student's learning effect. Item Response Theory suggests that the access to the students' potential characteristics can be obtained through the results of the examinee's answers to the test questions and that the test questions have a certain level of difficulty and differentiation. The model uses a difficulty indicator to measure the degree of difficulty of a test question, with larger values indicating that the question is more difficult. The differentiation index is used to measure the differentiation of the test question, which refers to the identification of the level of competence of the test question for all the students tested, and the larger the value indicates the greater the difference in the students' scores. The mathematical formulas for the single and double three-parameter methods of item response theory are shown in (1), (2), and (3), respectively:

$$p\left(u_{ij}=1\middle|\theta_i\right)=\frac{e^{(\theta_i-d_j)}}{1+e^{(\theta_i-d_j)}} \tag{1}$$

$$p\left(u_{ij}=1\middle|\theta_i,a_j\right)=\frac{1}{1+e^{-Ca_j(\theta_i-d_j)}} \tag{2}$$

$$p\left(u_{ij}=1\middle|\theta_i,a_j,g_j\right)=g_j+\frac{1-g_j}{1+e^{-Ca_j(\theta_i-d_j)}} \tag{3}$$

where: θ_i denotes the degree of mastery of the knowledge points by student i . a_j is the differentiation parameter of the test question. d_j is the difficulty parameter of the test questions. g_j is the guessing degree parameter. Currently the most commonly used response function in the field of education is the three-parameter response function.

2.1.2. Deterministic Input Noise and Gate Models

The excellent interpretability and extensibility of DINA have made it the most widely used method in cognitive diagnosis.The properties of DINA make it very suitable for the prediction of scores on dichotomous items.The mathematical expression of the DINA model is shown in Equation (4):

$$p\left(X_{ij}=1\middle|\theta_i\right)=g_j^{1-\pi_{ij}}\left(1-s_j\right)^{\pi_{ij}},\pi_{ij}=\prod_{k=1}^{K}\theta_{ik}^{q_{jk}} \tag{4}$$

where: X_{ij} denotes the result of student i 's answer to test question j , $X_{ij}\in\{0,1\}$. g_j,s_j are the guess factor and the miss factor for test question j , respectively. π_{ij} denotes the summary of students' i mastery of the knowledge of the exercise j . θ_i is a vector of students' i knowledge point mastery. q_j is the vector of knowledge points examined for test question j . When learner i has mastered all the examined knowledge points of exercise j , π_{ij} takes 1, otherwise it is 0.

2.2. Neural Collaborative Filtering

The Neural Collaborative Filtering model (NeuCF) fuses neural networks with collaborative filtering algorithms. The input layer inputs one-hot vectors of users and items, and passes through an embedding layer to get the embedding information of user u and item i . After that the model models the user and item in two lines: first the embedding representations of the user and item are passed through a fully connected layer, which outputs the potential vector of the user and the potential vector of the item. Then, the two latent vectors are linked in a specific way as inputs to the last multiple hidden layers, and the prediction score y is output after learning the latent representations of the user-item interactions.The mathematical definition of the NCF is shown in Equation (5):

$$\hat{y}_{ui}=\Phi_{out}\left(\Phi_x\left(\cdots\Phi_2\left(\Phi_1\left(p^TU_u,Q^Tv_i\right)\right)\cdots\right)\right) \tag{5}$$

where: Φ_{out} and Φ_x denote the mapping function between the output layer and the x th NCF layer, and P and Q are the implied feature matrices of the user and the item, respectively.

2.3. Neuromatrix decomposition model

The Neural Matrix Factorization (NMF) model is a neural network-based recommendation model that, unlike traditional matrix factorization methods, fuses Generalized Matrix Factorization (GMF)-based and Multi-Layer Perceptron (MLP)-based recommendation models according to a neural collaborative filtering framework. The Neural Matrix Factorization (NMF) model is a neural network-based recommendation model that, unlike traditional matrix factorization methods, fuses Generalized Matrix Factorization (GMF)-based and Multi-Layer Perceptron (MLP)-based recommendation models according to a neural collaborative filtering framework.

The structure of the neuromatrix decomposition model is shown in Figure 1, which models the interaction between users and items, with the output of each layer serving as the input to the next layer. First, the inputs in the model input layer are represented by uniquely hot coded vectors for user u and item i . After that, the sparse vectors in the input layer are mapped into dense vectors by two embedding layers embedding, which get the user potential vector p_u and the project potential vector q_i , respectively. dense vectors are better than sparse vectors and can better deal with data sparsity. the

GMF part is mainly based on the idea of matrix decomposition, and the embedding vectors of the user and the project p_u^{GMF} and q_i^{GMF} are subjected to dot-product operation to obtain the output ϕ_{GMF} of the GMF part. This approach can effectively mine the interaction information between the user and the project, but ignores the nonlinear relationship between the user and the project.The MLP part is based on the structure of the multilayer perceptual machine, which learns and interacts the embedding vectors of the user and the project p_u^{MLP} as well as q_i^{MLP} through multiple fully-connected layers, and obtains the outputs of the MLP part ϕ_{MLP} . This approach can effectively mine the nonlinear relationship between users and items, but ignores the interaction information between embedding vectors.The NMF layer mainly splices the results ϕ_{GMF} and ϕ_{MLP} of the GMF part and the MLP part, and learns and interacts them through one fully-connected layer to obtaining the final predicted scores. Overall, the neuromatrix decomposition model combines the advantages of the GMF part and the MLP part, fully exploits the interaction information and nonlinear relationship between the user and the item, and improves the accuracy of recommendation. Therefore, the neural matrix decomposition model can be applied to teaching resources recommendation, but the method still ignores the personalized learning information of students, which in turn affects the effectiveness of recommendation.

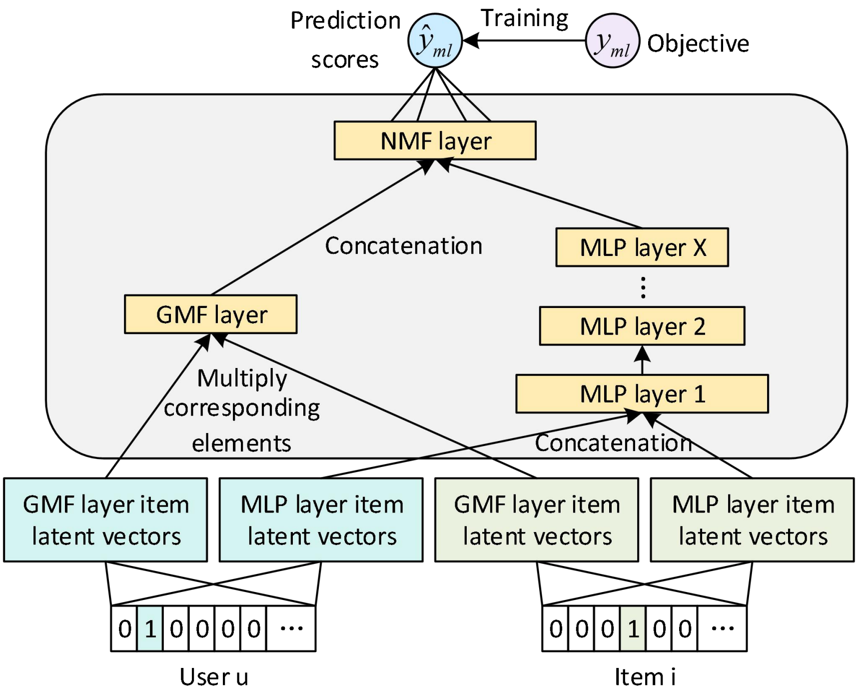

Figure 1. Neural matrix factorization model

2.4. MNCD-NMF model specific process

The method possesses both the accuracy of collaborative filtering methods and the interpretability of cognitive diagnostic modeling. The overall flow of the model is shown in Figure 2, which first outputs the students' knowledge mastery through cognitive diagnostic modeling and calculates the students' personalized learning characteristics. After that, the students' personalized learning characteristics are integrated into the neural matrix decomposition method to predict the probability of students answering the test questions correctly (i.e., the students' predicted scores). Finally, appropriate teaching resources are recommended to students based on the probability of answering correctly and the set difficulty range of test questions. In this paper, we propose a personalized teaching resource recommendation method based on multifactor neurocognitive diagnosis and neural matrix factorization (MNCD-NMF). Compared with traditional recommendation methods, this method uses the information of test questions, students, and knowledge points to predict the students' performance from the perspective of their individualized learning characteristics and the common characteristics of similar groups of students, and recommends appropriate teaching resources to the students.

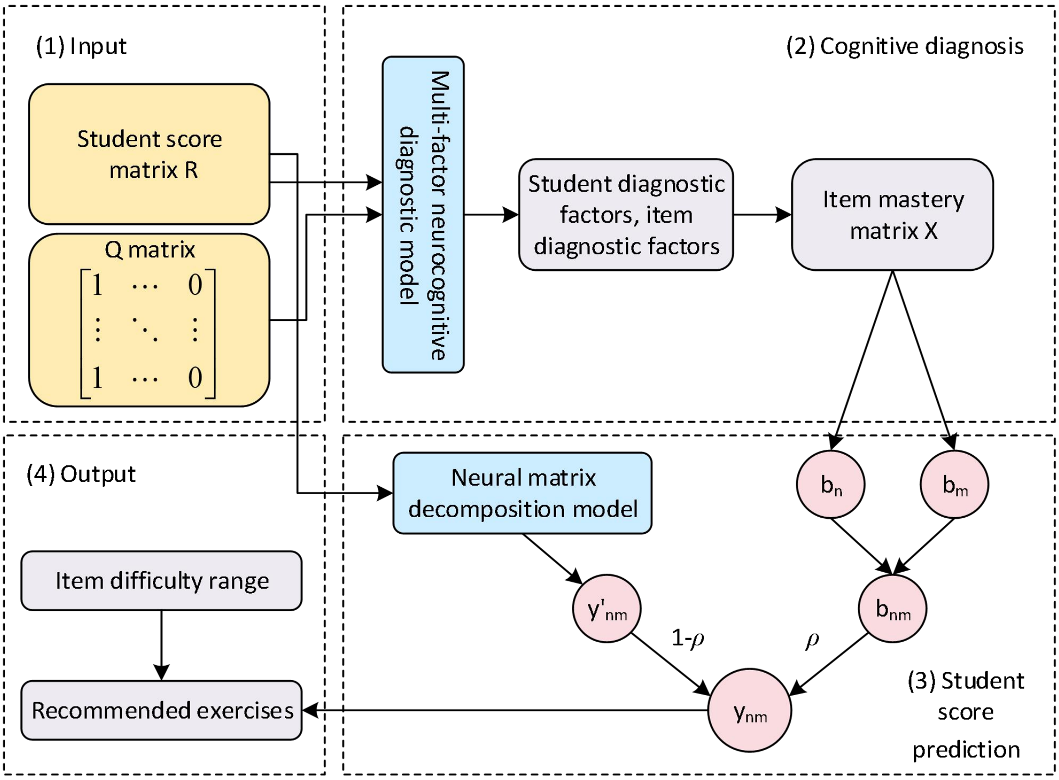

Figure 2. Process of the NMCD-NMF model

Step 1: Student cognitive diagnosis

In the Student Cognitive Diagnosis section, the first step is to perform unique heat coding on the set $S=\{s_1,\ldots,s_N\}$ with N students and the set of M test questions $E=\{e_1,\ldots,e_M\}$ in order to obtain the students' and test questions' The solo thermal encoding matrices of $U=(u_1,u_2,\ldots,u_N)^{\mathrm{T}}$ and $I=(i_1,i_2,\ldots,i_M)^{\mathrm{T}}$, respectively. After that, the unique heat coding vector u_n of the students n, the unique heat coding vector i_m of the test questions m, and the expert-labeled knowledge point correlation matrix Q are used as inputs to the MNCD model, where $u_n \in \{0,1\}^{1\times N}, i_m \in \{0,1\}^{1\times M}$. Since the MNCD model predicts students' mastery of knowledge points by iteratively updating the parameters of the diagnostic factors of students and test questions, the final output of the students' mastery matrix X contains the feature information of all the diagnostic factors, which in turn can be used to extract the students' personalized learning features.

The MNCD-NMF method considers that students' performance on test questions is affected by two factors: students' individualized learning characteristics and common learning characteristics of the student group, from which students' individualized learning characteristics b_{nm} can be extracted according to the students' knowledge point mastery level matrix X:

$$X=\begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \vdots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{6}$$

$$b_{nm}=b_n+b_m=\frac{1}{M}\times\sum_{j=1}^{M}X_{nj}+\frac{1}{N}\times\sum_{j=1}^{N}X_{jm} \tag{7}$$

where M is the number of test questions, N is the number of students, b_n is the mean of the n th row of the knowledge point mastery level matrix X, which represents the difference in overall knowledge point mastery among students. And b_m is the mean value of the m th column of the knowledge point mastery level matrix X, which reflects the difference in difficulty level between different test questions. They can accurately reflect students' individualized learning status and provide the basis for subsequent prediction of students' scores in combination with the neuromatrix decomposition model.

Step 2: Score prediction by integrating students' individuality and commonality

The student score prediction part of the MNCD-NMF method, i.e., the neuromatrix decomposition model after incorporating students' individualized learning characteristics. After obtaining the information b_{nm} of students' individualized learning characteristics through the multifactor neurocognitive diagnostic model, it is incorporated into the output part of the neuromatrix decomposition model.

By leveraging the special network structure of the MLP framework to better explore the potential relationships between students and questions, the input layer consists of one-hot encoded vectors u_n and i_m for students and questions respectively. Thus, the embedding vectors obtained in the embedding layer can be regarded as the potential vectors of students and questions in the MLP part, ρ_n^{MLP} and q_m^{MLP}, and then input into multiple fully connected layers:

$$\phi_1^{MLP} = f_1\left(W_1^T\begin{bmatrix}\rho_n^{MLP}\\ q_m^{MLP}\end{bmatrix} + b_1\right) \tag{8}$$

$$\phi_2^{MLP} = f_2\left(W_2^T\phi_1^{MLP} + b_2\right) \tag{9}$$

$$\phi_3^{MLP} = f_3\left(W_3^T\phi_2^{MLP} + b_3\right) \tag{10}$$

where W_1, W_2, W_3 are the weight matrices of the neural network, b_1, b_2, b_3 are the bias vectors in the neural network, f_1, f_2, and f_3 denote the corresponding activation functions of each layer of the neural network, which can be chosen from the sigmoid, tanh, and ReLU functions, and in this paper, we choose ReLU as the activation function. In the GMF section, the one-hot encoded vectors u_n and i_m of the students and the questions are still input into the embedding layer of the GMF section to obtain the latent feature vectors ρ_n^{GMF} and q_m^{GMF} of the students and the questions, and the inner product is performed to obtain the correlation between the students and the questions. The calculation formula of the GMF section is as follows:

$$\phi^{GMF} = \rho_n^{GMF} \circ q_m^{GMF} \tag{11}$$

where the symbol $\circ$ denotes multiplication by elements.

In order to improve the generalization ability of the model, the dimensions of the input vectors of the MLP and GMF layers are kept different, which means that the MLP layer can contain more hidden layers. Then, the output of the final hidden layer of the MLP layer is connected to the output of the GMF layer through the NMF layer, which realizes the feature modeling combining the linearity of matrix decomposition and the nonlinearity of neural network, demonstrating the powerful expressive ability of the model, which enables a more accurate prediction of students' scores:

$$y'_{nm} = \sigma\left(h^{\mathrm{T}}\begin{bmatrix}\phi^{GMF}\\ \phi_3^{MLP}\end{bmatrix}\right) \tag{12}$$

where h^T denotes the weight matrix of the output layer of the fusion model, and σ denotes the sigmoid function, which serves to map the value of the predicted student's score between 0 and 1.

After that, the personalized learning features b_{nm} about the students are combined with the common learning features y'_{nm} about the students to obtain the final predicted scores of the students on the test questions:

$$y = \rho b_{nm} + (1-\rho)y'_{nm} \tag{13}$$

where ρ is a parameter with a value range of $[0,1]$. In predicting students' test scores y, the parameter ρ is used to regulate the proportion of students' individualized learning characteristics and students' common learning characteristics. A larger ρ indicates that the student's predicted score is more influenced by the student's individualized learning characteristics. Conversely, a smaller ρ

indicates that the student's predicted score is more influenced by the student's common learning characteristics. In particular, when $\rho = 0$, the model degenerates to a neuromatrix decomposition approach, i.e., no individualized learning characteristics of students are introduced. Finally, the loss function of the neuromatrix decomposition model incorporating students' individualized features is the cross-entropy between the output y and the students' real answer records r :

$$loss = -\sum_i \left(r_i \log y_i + (1 - r_i) \log(1 - y_i) \right) \tag{14}$$

Step 3: Recommendation of Instructional Resources Based on Difficulty Range

Through the above work, it is necessary to recommend personalized teaching resources to students based on their predicted probability of answering correctly (i.e., students' predicted scores) in this step. Different from the traditional collaborative filtering recommendation algorithm, which only recommends teaching resources based on the similarity of students' preferences and interests, this paper adopts a method that can set a difficulty range to generate a list of recommended teaching resources based on students' learning ability. First, a difficulty range $[\beta_1, \beta_2]$, where $\beta_1 < \beta_2$, needs to be set. After that, based on the predicted probability y of students' correct answers in the previous step, the set of teaching resources E_s in the list of teaching resources to be recommended where the predicted probability of students' correct answers is in the numerical interval $[\beta_1, \beta_2]$ is recommended to the students.

3. Experimentation and evaluation

3.1. Data sets

In this paper, a total of 385,457 responses were collected from the Smart Classroom Online Teaching Guangdong Teaching Cloud Platform, named DATA0 dataset, which was statistically determined to contain a total of 62 knowledge points, 338 student users, and 5,866 teaching resources after being organized. In addition, this paper also uses FrcSub dataset as well as Math1 and Math2 datasets. In order to unify the naming, the Math1 dataset is named DATA1 dataset, the Math2 dataset is named DATA2 dataset, and the FrcSub dataset is named DATA3 dataset. The DATA1 and DATA2 data sets are composed of two parts: student test score data and test question-knowledge point correlation matrix data.The DATA3 data set mainly contains student-test score data and test question-knowledge point correlation data.The part of the test score data of the student users has the score data of the 566 student users on 25 test questions, which is expressed by using the 0/1 scoring method, with 1 indicating the correct answer to the test question and 0 indicating the correct answer to the test question and 1 indicating the correct answer to the test question. The test question-knowledge point correlation matrix includes the correlation between the 25 test questions and 10 knowledge points, also using 0/1 to represent the correlation, 1 if the test question examines the knowledge point, and 0 if it does not. The descriptive statistics for each data set are shown in Table 1.

Table 1. Dataset statistical information

Dataset	The number of students	The number of teaching resources	Knowledge points
DATA0	338	5866	62
DATA1	4362	25	12
DATA2	4082	25	15
DATA3	566	25	10

3.2. Evaluation indicators

In this paper, the data are divided into training dataset as well as test dataset according to a certain proportion and assigned randomly, i.e., each data sample is used with the same probability as training data or test data. In this paper, the training dataset is used to train the parameters in the personalized recommendation method of teaching resources based on MNCD-NMF model, and the test dataset is used to evaluate the recommendation effect of the algorithm. In terms of evaluation metrics, this paper adopts commonly used metrics in recommender systems, including accuracy rate, recall rate, and F1 metrics, to evaluate the recommendation effect of the teaching resource recommendation algorithm based on the MNCD-NMF model on the recommendation of teaching resources. Among them, the F1 value combines the accuracy rate $\Pr ecison$ and the recall rate $Recall$, and the higher the F1 value, the higher the accuracy rate of the recommendation algorithm. The specific accuracy rate, recall rate and the mathematical expression of F1 value are defined as shown in equation (15):

$$F1 = \frac{2 \times \Pr ecison \times \operatorname{Re} call}{\Pr ecison + \operatorname{Re} call}$$
$$\Pr ecison = \frac{|R \cdot Y|}{|R|}, \operatorname{Re} call = \frac{|R \cdot Y|}{|R|} \tag{15}$$

where *Precison* denotes the proportion of the recommended teaching resources that are truly suitable for the student users, and *Recall* denotes the proportion of the recommended teaching resources that are compatible with the student users to all the resources in the test dataset. Y denotes the set of test question resources that can be correctly answered by student users in all the teaching resources associated under this knowledge set, and R denotes the result set of the recommended teaching resources.

3.3. Analysis of experimental results

In order to verify the effectiveness of the MNCD-NMF model-based recommendation algorithm proposed in this chapter on teaching resource recommendation, this paper conducts comparative experiments between the MNCD-NMF model recommendation algorithm and some classical teaching resource recommendation methods, including the User-Based (UB) collaborative filtering (CF) recommendation method, the Cognitive Diagnostic Deterministic Input Noise and Gate Model (DINA) recommendation method, Probability Matrix Decomposition with Cognitive Diagnostics (PMF-CD) teaching resource recommendation method, and Joint Probability Matrix with Cognitive Diagnostics (QueRec) recommendation method.

In the experimental process, in order to observe the effect of different data sparsity on each recommendation algorithm, this paper extracts 70%, 50%, 30%, and 10% from all datasets as the test dataset, and the rest as the training dataset. That is, when 70% of the data are randomly extracted as test data, it means that the remaining 30% is used as the training set to predict the test data, and the same is true for 50%, 30% and 10%. In addition, this paper uses the difficulty value of 0.6 as the boundary to classify teaching resources into two categories: simple teaching resources and complex teaching resources, and conducts a comparative experiment on the recommendation effect of teaching resources with different difficulty levels, in which the difficulty of the test question resources is statistically derived from students' historical response data counted in multiple tests, and the rest of the video teaching resources and text teaching resources are manually labeled by the domain experts or teachers who generate the resources.

In the experiment, 3 sets of simple teaching resources and 3 sets of complex teaching resources were recommended to the students respectively, and the CUPMF modeling method was compared with the other three methods in the experiment. Experiments on the above algorithms were conducted using training sets with different sparsity levels, and the predicted results of simple teaching resources F_1 values and the predicted results of complex teaching resources F_1 values are shown in Tables 2 and 3, respectively.

As the proportion of the test set decreases, i.e., the proportion of the training set increases, the MNCD-NMF model outperforms the other four algorithms in terms of recommendation accuracy for simple teaching resources as well as complex teaching resources as a whole. Specifically, when recommending simple teaching resources F_1 values are 12.16% higher than the other four algorithms on average, and compared to the QueRec algorithm, the overall average improvement is 2.88%. When recommending complex teaching resources F_1 values improved by 12.29% on average over the other four algorithms, compared to the QueRec algorithm's overall average improvement of 2.98%. The above data shows that the MNCD-NMF method can effectively increase the recommendation accuracy and improve the recommendation effect.

Table 2. The simple teaching resource forecast the result F_1 value

Recommendation algorithm	Test set ratio				Mean accuracy
	70%	**50%**	**30%**	**10%**	
User-Based CF	0.505	0.518	0.514	0.491	0.5070
DINA	0.537	0.589	0.613	0.706	0.6113
PMF-CD	0.701	0.647	0.652	0.706	0.6765
QueRec	0.693	0.705	0.742	0.748	0.7220
MNCD-NMF	0.724	0.728	0.768	0.783	0.7508
Table 3 F_1 value of the prediction result for complex teaching resourcesRecommendation algorithm	Test set ratio				Mean accuracy
	70%	50%	30%	10%	
User-Based CF	0.488	0.61	0.591	0.602	0.5728
DINA	0.679	0.671	0.699	0.736	0.6963
PMF-CD	0.686	0.718	0.726	0.765	0.7238
QueRec	0.753	0.768	0.811	0.822	0.7885
MNCD-NMF	0.785	0.786	0.836	0.866	0.8183

4. Intercultural communication integration teaching model

Taking business English learning as the center and the enhancement of intercultural communication ability as the goal, the MNCD-NMF-based personalized teaching resources recommendation method is introduced, and the intercultural communication integration teaching mode is proposed. The teaching mode is shown in Figure 3. This teaching mode can understand students' learning objectives and knowledge levels by analyzing their learning data, such as learning records and classroom practice scores. Combined with the proposed MNCD-NMF personalized teaching resource recommendation method based on MNCD-NMF, it can generate personalized learning path recommendations for students, including the recommendation of learning resources that are suitable for their knowledge level and learning goals. Incorporating the cultivation of intercultural communication skills in the learning process, integrating it organically with the language skill objectives, contents and requirements of the Business English course, cultivating intercultural skills and acquiring intercultural knowledge. In teaching, teachers should not only impart language knowledge, but also cultivate students' sensitivity and insight to cultural differences, understand the cultural connotations carried by the language, enhance the ability to think critically, and improve cross-cultural communicative competence while improving language skills. The teaching model is shown in Figure 3.

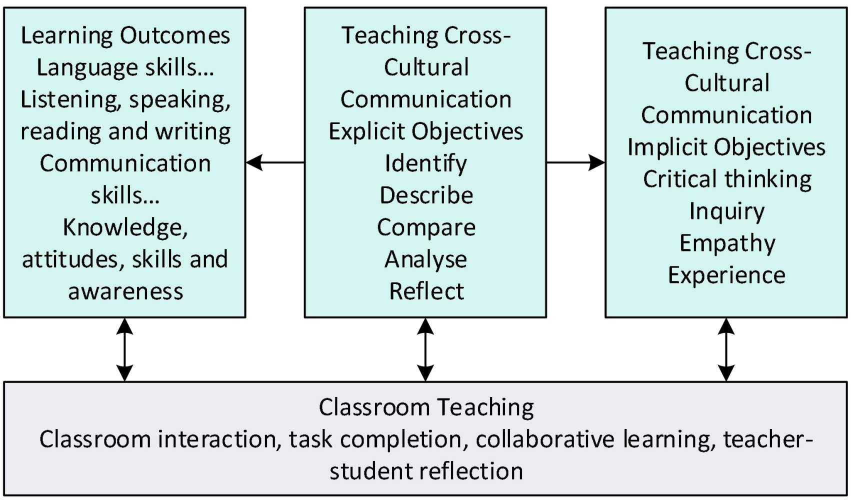

Figure 3. Cross-cultural Communication Integrated Teaching Model

Under the cross-cultural communication integrated teaching mode, teachers focus on cultivating students' ability to interpret and relate to different cultures, to appreciate different ways of behavior, modes of thinking, customs and taboos, to raise awareness of cultural differences, to pay attention to the content of cross-cultural communication, and to motivate students to make in-depth comparisons, analyses and reflections on different cultures.

5. Teaching experiment design and analysis of results

This study adopts a teaching model incorporating the MNCD-NMF algorithm to conduct a teaching experiment on the cultivation of intercultural communicative competence, aiming to investigate the effect of using the intercultural communicative integration teaching model based on the MNCD-NMF personalized teaching resource recommendation method in the teaching of business English on the cultivation of intercultural communicative competence of college students.

5.1. Subject of the study

The research subjects of this experiment are the students majoring in Business English in H college. The experimental class, totaling 52 students, was chosen to be taught with the intercultural communication integration teaching mode designed in this paper. A control class totaling 52 students was chosen to be taught with the traditional 3P teaching method. In this study, the results of the two classes' business English preliminary examination scores were comparatively analyzed by independent samples t-test, and the results showed that $p>0.05$, indicating that there is no significant difference between the scores of the two classes, and that the students of the two classes are at a comparable level of English proficiency, so that comparative experiments can be carried out.

In this study, according to the English midterm scores (out of 100 points), students are divided into three different English levels: high (80 points and above), medium (60-80 points), and low (below 60 points). Information on the distribution of the number of students in the experimental and control classes is shown in Table 4.

Table 4. Information of Students in the Experimental Class and the Control Class

	Total number of people	**Male**	**Female**	**High level**	**Medium level**	**Low level**
Experimental Class	52	16	39	10	24	21
Control class	52	18	34	11	20	21

5.2. Research tools

This study collects data through college students' intercultural communication competence test papers and interviews, and analyzes the data with SPSS26.0 software to investigate the effect of contextual teaching method in the cultivation of college students' intercultural communication competence, and the specific research work is as follows:

(1) Intercultural communication competence test paper

The intercultural communicative competence test paper used in this study is based on the contents of the intercultural communicative competence test paper for college students designed in the "Survey and Reflection on English Intercultural Communicative Competence" and the "Survey and Research on the Status of English Intercultural Communicative Competence". In order to make the test paper truly reflect the intercultural communicative competence of college students, 39 college students outside the experimental and control classes were randomly selected for testing before the experiment to check the reliability and validity of the test paper. After analyzed by SPSS26.0, the author measured that the Alpha coefficient is 0.883, which is greater than 0.7, and the KMO value is 0.812, which is greater than 0.6, so the reliability of this test paper is better.The results of the KMO and Bartlett's test are shown in Table 5.

Table 5. KMO and Bartlett tests

The measurement of the suitability of KMO sampling		**.812**
Bartlett sphericity test	113.722	113.722
	38	38
	.000	.000

The intercultural communicative competence test paper for college students used in this study consisted of 36 questions including 4 dimensions namely knowledge, awareness, emotion, and behavior. The scale is in the form of a Likert scale with responses ranging from 1 (strongly agree) to 5 (strongly disagree). Table 6 shows the design dimensions, the number of questions1 and the distribution of questions in the intercultural communication competence test paper for college students.

Table 6. Basic Information of the Intercultural Communication Ability Test Paper

Design Dimension	The number of items	Item distribution
Knowledge of English-speaking countries	9	1-9
Social values	9	10-18
Time concept	9	19-27
Social convention	9	28-36

In order to ensure that the test takers fill in the information truthfully and feel at ease in answering the questions, before the test, the author informed all the students in advance that this test paper would be used for academic research only, and that the test scores would not be disclosed to the outside world. The Intercultural Communication Competence Test was conducted twice at the beginning and the end of the semester.

(2) SPSS Software

SPSS is a series of software developed by IBM, which can be used for statistical and precise analysis of large-scale data.SPSS has been widely popularized and applied due to its advantages of easy operation, simple programming and powerful functions. The authors used this software in analyzing the data of this study to ensure the accuracy of the data and to produce accurate experimental results.

5.3. Data collection

The data of this study mainly comes from the intercultural communicative competence test paper scores of college students. The author collected intercultural communicative competence test paper data from students in the experimental and control classes before and after the experiment respectively.

Before and after the experiment, the intercultural communicative competence test paper was distributed twice in the experimental class and the control class, and the students in both classes were supervised to complete the responses in the self-study class. The test consisted of 36 multiple-choice questions, including four dimensions: knowledge, awareness, emotion and behavior. On both occasions, 107 copies of the intercultural communicative competence test papers for college students were distributed and 107 copies were returned, with a 100% return rate.

Finally, this study organizes and analyzes the data of intercultural communicative competence test papers of college students. The intercultural communicative competence test scores of students in the experimental and control classes before and after the experiment were entered into SPSS26.0 software for comparative analysis.

5.4. Experimental results and analysis

5.4.1. Analysis of pre-test data

The statistical descriptions of the pre-test data of the experimental and control classes are shown in Table 7. The mean values of intercultural communicative competence in the knowledge dimension of the experimental class and the control class before the experiment were 2.27 and 2.24, the mean values of intercultural communicative competence in the consciousness dimension were 2.13 and 2.22, the mean values of intercultural communicative competence in the affective dimension were 2.21 and 2.27, and the mean values of intercultural communicative competence in the behavioral dimension were 2.11 and 2.16, respectively.

Table 7. Statistical description of pre-test data

Variable	Group	Number	Average value	Standard deviation	Standard error mean
Knowledge	Experimental Class	52	2.27	0.2831	0.0261
dimension	Control class	52	2.24	0.2845	0.0366
Consciousness	Experimental Class	52	2.13	0.3022	0.0463
dimension	Control class	52	2.22	0.3258	0.0482
Emotional	Experimental Class	52	2.21	0.3125	0.0472
dimension	Control class	52	2.27	0.3863	0.0574
Behavioral	Experimental Class	52	2.11	0.2922	0.0401
dimension	Control class	52	2.16	0.2896	0.0396

Table 8 shows the results of independent samples t-test for the pre-test data of the experimental and control classes. There is no statistically significant difference between the data of the knowledge, awareness, emotion and behavior dimensions of the intercultural communicative competence scale of the experimental and control classes before the experiment, and the p-value is above the significance level of 0.05. It can be seen that the level of intercultural communicative competence of the two classes before the experiment is at the same level.

Table 8. Independent sample t-test for pre-test

		The same homosexual test		Mean equivalence t-test				
		F	**Sig**	**T**	**df**	**Sig(Double tail)**	**Mean difference**	**Standard error**
Knowledge dimension	Assumed equal variance	2.572	.117	0.663	108	.516	0.0318	0.0487
	Unassuming equal variance			0.665	98.323	.511	0.0379	0.0479
Consciousness dimension	Assumed equal variance	0.000	.995	-1.543	108	.131	-0.0981	0.0615
	Unassuming equal variance			-1.526	104.652	.128	-0.0937	0.0685
Emotional dimension	Assumed equal variance	1.532	.225	-1.029	108	.307	-0.0691	0.0677
	Unassuming equal variance			-1.026	103.831	.304	-0.0699	0.0613
Behavioral dimension	Assumed equal variance	0.132	.715	-0.842	108	.409	-0.0496	0.0595
	Unassuming equal variance			-0.834	106.724	.409	-0.0401	0.0584

5.4.2. Post-test data analysis

The pre-test independent samples t-test of the experimental and control classes is shown in Table 9. The mean values of intercultural communicative competence in the four dimensions of knowledge, awareness, and behavior in the experimental class after the experiment were 3.45, 3.37, 3.19, and 3.23, respectively. The mean values of intercultural communicative competence in the four dimensions of knowledge, awareness, and behavior in the control class were 2.25, 2.29, 2.20, and 2.27, respectively.

Table 9. Post-test Data of the Experimental Class and the control Class

Variable	Group	Number	Average value	Standard deviation	Standard error mean
Knowledge dimension	Experimental Class	52	3.45	0.4287	0.0469
	Control class	52	2.25	0.4297	0.0579
Consciousness dimension	Experimental Class	52	3.37	0.3859	0.0546
	Control class	52	2.29	0.3249	0.0689
Emotional dimension	Experimental Class	52	3.19	0.485	0.0521
	Control class	52	2.20	0.4235	0.0689
Behavioral dimension	Experimental Class	52	3.23	0.4247	0.0537
	Control class	52	2.27	0.3951	0.0487

The pre-test independent sample t-test of the experimental and control classes is shown in Table 10. After the experiment, there is a significant difference between the experimental class and the control class in the four dimensions of intercultural communicative competence, namely, knowledge, consciousness, emotion and behavior, and the posttest data of each dimension of the two classes is P=0.000, and the P value is lower than the significance level of 0.05, and the intercultural communicative competence of the experimental class students is higher than that of the control class students. This shows that the teaching mode of this paper is effective in improving the cross-cultural communicative competence of business English of college students.

Table 10. Post-test independent sample t-test

		The same homosexual test		Mean equivalence t-test				
		F	**Sig**	**T**	**df**	**Sig(Double tail)**	**Mean difference**	**Standard error**
Knowledge dimension	Assumed equal variance	2.566	.112	13.642	108	.000	1.03171	0.04842
	Unassuming equal variance			13.642	97.454	.000	1.03189	0.04818
Consciousness dimension	Assumed equal variance	.000	.993	11.532	108	.000	1.09339	0.06089
	Unassuming equal variance			11.537	106.892	.000	1.09347	0.06106
Emotional dimension	Assumed equal variance	1.535	.225	9.027	108	.000	1.06888	0.06702
	Unassuming equal variance			9.027	103.871	.000	1.06903	0.06701
Behavioral dimension	Assumed equal variance	0.128	.725	15.842	108	.000	1.04708	0.05604
	Unassuming equal variance			15.838	105.654	.000	1.04701	0.05595

5.4.3. Changes in different dimensions of intercultural communicative competence

(1) Changes in the knowledge dimension of intercultural communication competence

From the independent samples t-test, the experimental class and the control class are at the same level in the knowledge dimension before the experiment, but the difference is obvious after the experiment, the mean is 3.45 and 2.25 respectively, the standard deviation is 0.4287 and 0.4297 respectively, and the result of the t-test of equal means shows T=13.642, P=0.000, and the P-value is lower than the level of significance of 0.05. Therefore, the difference in the knowledge dimension of intercultural communicative competence between the experimental class and the control class after the experiment is more significant. The difference between the experimental class and the control class in terms of the knowledge dimension of intercultural communicative competence is relatively significant, and the level of intercultural communicative competence of the students in the experimental class after the experiment is significantly higher than that before the experiment.

The paired samples test for the knowledge dimension of the experimental and control classes is shown in Table 11. From the paired samples t-test, the results of the paired samples t-test of the control class in the pre- and post-test of the knowledge dimension show T=-0.062, P=0.963, and the P-value is higher than the significance of 0.05, so that there is no significant difference in the pre- and post-test scores of the control class in the knowledge dimension. The results of the paired samples t-test for the pre and post-test of the knowledge dimension of the experimental class show $P<0.05$, which shows that there is a significant difference in the pre and post-test scores of the experimental class before and after the experiment, and that the post-test scores of the experimental class are better than the pre-test scores.

Table 11. Paired sample testing of knowledge dimensions

		Pairing difference							
		Mean value	**Standard deviation**	**Standard error mean**	**The difference is 95% confidence interval**		**T**	**df**	**Sig(Double tail)**
					Lower limit	**Upper limit**			
Laboratory class	premeasurement - Post-test	-1.18	0.45936	0.0638	-1.3015	-1.0475	-18.621	53	.000
Control class	premeasurement - Post-test	-0.01	0.4472	0.0611	-.1246	.1168	-.062	55	.963

(2) Changes in the awareness dimension of intercultural communication competence

The paired samples test for the consciousness dimension of the experimental and control classes is shown in Table 12. The results of the paired-samples t-test for the pre- and post-tests of the consciousness dimension of the control class showed that the p-value was above the significance of

0.05, so there was no significant difference in the pre- and post-test scores of the consciousness dimension in the control class. The paired samples t-test results of the pre- and post-tests of the consciousness dimension in the experimental class show T=-17.663, P=0.000. It can be seen that there is a significant difference between the pre- and post-test scores of the experimental class in the consciousness dimension before and after the experiment, which means that the post-test scores of the experimental class in the consciousness dimension are significantly better than the pre-test scores.

Table 12. Consciousness dimension paired sample test

		Pairing difference							
		Mean value	**Standard deviation**	**Standard error mean**	**The difference is 95% confidence interval**		**T**	**df**	**Sig(Double tail)**
					Lower limit	**Upper limit**			
Laboratory class	premeasurement - Post-test	-1.24	.5116	.0705	-1.3833	-1.1014	-17.663	52	.000
Control class	premeasurement - Post-test	-.07	.4412	.0585	-.1925	.0472	-1.232	54	.236

(3) Changes in the affective dimension of intercultural communicative competence

The paired samples test for the affective dimension of the experimental and control classes is shown in Table 13. The results of the paired-samples t-test for the pre- and post-tests of the affective dimension of the control class showed P=0.25>0.05, so there was no significant difference in the pre- and post-test scores of the affective dimension of the control class. The paired samples t-test results of the pre- and post-tests of affective dimension in the experimental class show T=-13.864, P<0.05, which shows that there is a significant difference between the pre- and post-test scores of the experimental class before and after the experiment, indicating that the post-test scores of the affective dimension of intercultural communication competence of the experimental class students are significantly better than the pre-test scores.

Table 13 Emotional dimension paired sample test

		Pairing difference							
		Mean value	Standard deviation	Standard error mean	The difference is 95% confidence interval		T	df	Sig(Double tail)
					Lower limit	Upper limit			
Laboratory class	premeasurement - Post-test	-.98	.5188	.0719	-1.1322	-.8467	-13.864	52	.000
Control class	premeasurement - Post-test	.07	.4866	.0657	-.0556	.2083	1.173	54	.255

(4) Changes in the behavioral dimensions of intercultural communication competence

The paired samples test of the behavioral dimensions of the experimental and control classes is shown in Table 14. The paired samples t-test results of the pre- and post-tests of the behavioral dimensions of the control class showed T=-1.770, P=0.062, P value higher than the significance of 0.05, which shows that the differences in the pre- and post-test scores of the control class in the behavioral dimensions are not too obvious. The paired-sample t-test results of the pre- and post-tests of the behavioral dimension of the experimental class show that T=-16.387, P=0.000, P-value is lower than the significance 0.05. Therefore, there is a more significant difference between the pre- and post-test scores of the behavioral dimension of the students in the experimental class before and after the experiment, and it also indicates that the post-test scores of the experimental class in the behavioral dimension are significantly higher than the pre-tests, so this paper's cross-cultural communicative integration teaching mode has a significant impact on enhancing intercultural communication competence of business English for college students is obvious effect.

Table 14. Behavioral dimension paired sample test

		Pairing difference							
		Mean value	Standard deviation	Standard error mean	The difference is 95% confidence interval		T	df	Sig(Double tail)
					Lower limit	Upper limit			
Laboratory class	premeasurement - Post-test	-1.12	.4988	.0687	-1.2598	-.9828	-16.387	52	.000
Control class	premeasurement - Post-test	-.11	.4285	.0565	-.2287	-.0029	-1.771	54	.062

6. Conclusion

Intercultural communication in the context of globalization puts forward an urgent demand for business English talents in colleges and universities. In view of this, this study tries to apply the intercultural communication method based on personalized teaching resource recommendation algorithms to English classrooms in colleges and universities, and proposes a personalized test question recommendation method based on cognitive diagnosis and collaborative filtering called MNCD-NMF in order to explore its Role. The study draws the following conclusions:

(1) In the algorithm performance test empirical demonstration, it turns out that the MNCD-NMF model proposed in this paper is better than the four algorithms in comparison in the recommendation accuracy of teaching resources overall. When recommending simple teaching resources and when recommending complex teaching resources, its F_1 value is improved by 12.16% and 12.29% on average compared with the other four algorithms on the whole, which verifies that the MNCD-NMF method proposed in this paper is able to effectively increase the recommendation accuracy of teaching resources and improve the recommendation effect.

(2) Through the independent sample t-test of the pre-test of the experimental class and the control class, it can be seen that there is a significant difference between the experimental class and the control class in the four dimensions of intercultural communicative competence, namely, knowledge, awareness, emotion and behavior, and the post-test data of the two classes in all dimensions is P=0.000, and the P value is lower than the level of significance of 0.05. It can be seen that this paper can promote the penetration of cross-cultural knowledge, cultivate the openness of the students to intercultural communicative awareness, increase emotional responses in intercultural communication, and improve the positivity of intercultural communicative behavior.

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