International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-17
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Article

Research on the Promotion Strategies of English Intercultural Communicative Competence Transfer in Colleges and Universities Supported by Artificial Intelligence

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Abstract: In order to better cultivate students' cultural adaptability to cope with the challenges brought by globalization, and at the same time to improve the quality of teaching in order to discover more effective teaching methods, the article explores the promotion strategy of English intercultural communicative competence transfer in colleges and universities with the support of artificial intelligence. It proposes a cross-cultural learning resource recommendation model for English in colleges and universities that combines generative adversarial network and collaborative filtering model, and then introduces the conceptual mapping concept to construct an English cross-cultural communicative competence cultivation model from five aspects: theoretical foundation, teaching goal, operation procedure, realization conditions and evaluation. Software concept maps and paper-and-pencil concept maps have different roles in cultivating primary school students' intercultural communicative awareness, knowledge and competence, with significant differences in intercultural communicative awareness and knowledge dimensions ($P<0.05$). The results of the content analysis and case study indicate that the software concept map is more scalable and facilitates cooperative learning and mutual evaluation among students. The research in this paper is conducive to the cultivation of intercultural communicative competence of college students, and it has advantages in cultivating intercultural communicative competence compared with traditional college English teaching.

Keywords: generative adversarial network; collaborative filtering model; concept map; intercultural communicative competence

1. Introduction

According to the latest Report on Sino-foreign Cultural Exchanges 2023 released by the Foreign Languages Bureau of China, Sino-foreign cultural exchanges in 2023 showed a remarkable recovery trend and a positive pattern of development. The scale of exchanges has recovered to more than 90% of the pre-epidemic level, and breakthroughs have been made in the mode of exchanges, presentation forms and depth of dialogues, and Chinese-foreign cultural exchanges have stepped into a new stage of high-quality development [1]. This indicates that in the strategic context of the construction of cultural confidence in the new era, the cultivation of cross-cultural talents with international vision has become an important direction of higher education reform [2]. At present, with the acceleration of the globalization process, intercultural communication ability is not only the core competitiveness of individual career development, but also the key element to promote the innovative development of society and the promotion of civilization mutual understanding [3]. For college students, while consolidating their professional foundation, systematically improving intercultural communication skills has become an inevitable requirement for talent cultivation [4]. Especially in the context of the rapid development of artificial intelligence technology, how to effectively integrate intelligent technology resources, innovate the cultivation mode of intercultural communicative competence, and build a new talent cultivation system with global vision and intercultural competence is an important issue that needs to be solved in higher education.

Regarding the definition of intercultural competence, scholars in different fields have expressed it differently. Literature [5] defines intercultural competence as an individual's ability to effectively adapt, participate and behave appropriately in intercultural communication by integrating cognitive knowledge, abilities, attitudes, traits, performance and behavioral skills, and by combining cultural experience and foreign language knowledge; its composition covers cognitive, affective, and behavioral dimensions, and is manifested through both internal qualities and external performances, which ultimately realizes effective communication and adaptation in intercultural situations. The final goal is to realize effective communication and adaptation in cross-cultural situations. Literature [6] suggests that intercultural competence can be defined from two perspectives: as a set of traits possessed by an individual, and as a level of professional skills for learning, applying and creating intercultural knowledge. Literature [7] suggests that intercultural competence is a multidimensional literacy required for individuals to participate effectively in intercultural interactions in the context of globalization, which is manifested both in cultural intelligence (including metacognitive, cognitive, motivational and behavioral dimensions) and in the stage-by-stage developmental level of intercultural competence. Its core lies in the integration of cognitive, affective and behavioral dimensions to achieve effective understanding, adaptation and communication in cross-cultural situations. Literature [8] considers intercultural competence to be the multidimensional literacy required for individuals to interact effectively in intercultural situations, which has gradually shifted to the evolution of a dynamic system of skills and competencies, with cultural intelligence as an important theoretical extension reflecting the higher-order characteristics of intercultural competence in the cognitive dimension. Literature [9] considers intercultural competence as an integrated literacy for individuals to understand the needs of the cultural environment and respond effectively in global work situations, which is manifested in core competencies such as cultural humility and ambiguity tolerance, and is reinforced through international experiences. As research continues to evolve and deepen, interpretations of its connotations change. However, researchers in various fields have gradually reached a consensus that “intercultural competence is a set of cognitive, affective, and behavioral skills and traits that support effective and appropriate interactions in different cultural contexts.”

The teaching of university English courses empowered by artificial intelligence is experiencing a stage of remodeling the teaching mode centered on the deep integration of technology and education [10]. With the power of artificial intelligence, the current university English course teaching has been greatly improved and progressed compared with the previous one in many dimensions, such as teaching efficiency, learning experience, educational equity and talent cultivation. Numerous scholars start from different theoretical perspectives, and literature [11] explores the construction and application of intercultural competence assessment model in AI education, theoretically explains the existing intercultural competence dimensions and evaluation scales through factor analysis, and constructs a comprehensive evaluation model that includes the principles and ideas of model construction, methods and steps, and model calculation. Literature [12] constructed an intelligent language learning system based on artificial intelligence technology, and the innovation of this system lies in the combination of multi-technology integration with personalized learning paths and real-time feedback mechanism, which provides an effective path to improve language proficiency and intercultural communication literacy. Literature [13] proposes four information technology-assisted learning strategies, namely, context construction, thematic resource interaction, scaffolding and human-computer-interpersonal feedback evaluation, and analyzes the learning data by combining edge computing and artificial intelligence algorithms, which verifies the significant effects of the above strategies on improving learners' intercultural awareness, critical thinking ability and English language proficiency. Literature [14] explores how technology-mediated English language teaching breaks through the limitations of traditional teaching on grammar and vocabulary and promotes the development of learners' intercultural competence through digital means such as interactive platforms, online collaboration, virtual simulation and artificial intelligence tools. Literature [15] improves the traditional MOOC based on cloud computing and artificial intelligence technology, and optimizes the traditional algorithm according to the actual teaching needs to propose an improved model, which can effectively enhance the efficiency of English intercultural teaching. Literature [16] proposes a cross-cultural intelligent language learning system (CILS), which provides a personalized learning experience adapted to learners' linguistic and cultural backgrounds through the integration of AI technology, and dynamically adjusts the content and methods to improve language proficiency and cross-cultural understanding.

Firstly, a GAN-based collaborative filtering recommendation model is proposed to generate user preference vectors by learning existing real user-item interactions and adding missing interaction information through a generative adversarial network. And two additional constraints are added to the generative model with the purpose of enhancing the ability of the generative model to mine the interaction information of users and items, so as to learn more accurate user preferences. Then the interactive advantage of concept map technology, a cognitive tool in teaching, is used to explore the construction of the interactive teaching model of English intercultural communicative competence in English colleges and universities from five aspects: theoretical foundation, teaching objectives, operational procedures, realization conditions and evaluation. Finally, through the teaching validation experiment, the teaching effect is verified from the aspects of students' intercultural communicative competence and the content of the work.

2. Recommendation of English intercultural communication resources in colleges and universities based on GAN

2.1. Collaborative filtering

The recommendation process of collaborative filtering based on learners is specified as follows:

Step 1: Construct the learner rating matrix, n represents the number of learners, m represents the number of learning resources, and R represents the learner rating matrix. The set of learners is $U=\{u_1,u_2,\ldots,u_n\}$, the set of learning resources is $I=\{i_1,i_2,\ldots,i_m\}$, and the ratings of learners u on the learning resources i are in the form of $R(i,j)\{i,j\mid i\in(1,n),j\in(1,m)\}$.

Step 2: Find the set of learners with the highest similarity to the target learner u. Based on the learner rating matrix R, calculate the similarity between learners. Use $Sim(u_1,u_2)$ to denote the similarity between learner u_1 and learner u_2. Sort the similarity between all other learners and the target learner u from high to low, and select the K learners that are most similar to the target learner from them, denoted by the set $S(u,K)$, and extract all the learning resources that the learner likes in S, and remove those that have already been rated by the learner u.

Step 3: Recommend learning resources for target learner u. The following formula is used to predict the degree of interest of learner u in learning resources i:

$$p(u,i)=\sum_{v\in S(u,K)\cap N(i)} sim_{uv}r_{vi} \tag{1}$$

where r_{vi} represents the interest level of learner v in learning resource i, $N(i)$ is the set of learners who have interacted with learning resource i, and sim is the inter-learner similarity between learner u and learner v. Finally, the highest rated N learning resources are selected from the set $P=\{p(u,i)\mid i\in N(i)\}$ to be recommended to the target learner u.

Collaborative filtering algorithm based on learning resources is based on the learning resources that learners have interacted with, and recommends other learning resources to learners based on the similarity between learning resources. The term “similar” here is actually more appropriate to use “related”, because collaborative filtering based on learning resources is based on co-occurrence to measure the similarity of learning resources, that is, through the behavior of the group of learners to measure whether the two learning resources are related to each other, rather than whether the two learning resources are related in some characteristics, that is, whether the two learning resources are related in some characteristics. whether two learning resources are similar in some characteristics.

Learning resource-based co-occurrence filtering works like this: the similarity between two of all learning resources is calculated by analyzing the interaction data of all learners with the learning resources, and then for a target learner u, the set of learning resources $I=\{i_1,i_2,\ldots,i_n\}$ that the learner u has interacted with is found by analyzing the historical interaction data of the learner u. Using the previously calculated similarity between learning resources, we can find the set of learning resources I' that are most similar to the learning resources in the set I but have not been interacted with by learner u, and then recommend the learning resources in the set I' to learner u.

Collaborative filtering based on learning resources can be divided into two steps:

Step 1: Calculate the two-by-two similarity between all learning resources and the two-by-two relevance of all learning resources through the learner rating matrix:

$$W_{ij} = \frac{|N(i) \cap N(j)|}{|N(i)|} \tag{2}$$

Among them, $|N(i)|$ represents the number of learners who have interacted with learning resource i, $|N(j)|$ represents the number of learners who have interacted with learning resource j, and $|N(i) \cap N(j)|$ represents the number of learners who have interacted with both learning resources i and j. The above formula can be interpreted as the proportion of learners who have interacted with learning resource i also interacting with learning resource j.

Step 2: For the target learner u, analyze the historical behavioral data of the learner u to find out his/her favorite set of learning resources $I = \{i_1, i_2, \ldots, i_n\}$, and generate the recommended set of learning resources for the target learner u. Based on the similarity between two by two of all learning resources calculated in Step1, the degree of interest of learner u in learning resource j can be predicted by the following formula:

$$P_{uj} = \sum_{i \in N(u) \cap S(j,K)} W_{ji} r_{ui} \tag{3}$$

where $N(u)$ is the set of learning resources that learner u is interested in, $S(j,K)$ is the set of K learning resources that have the highest relevance to learning resource j, W_{ji} is the relevance between learning resource j and learning resource i, and r_{ui} is the degree of real sense of interest that learner u has in learning resource i. From this formula, it can be seen that the more similar the learning resources are to the learning resources that the target learners are interested in, the more likely they are to be recommended to the target learners.

2.2. Generating Adversarial Networks

GAN is a deep learning model that consists of two parts, the generator and the discriminator.The core idea of GAN is to consider the generator and the discriminator as two opponents, the generator's goal is to generate data as realistic as possible, and the discriminator's goal is to distinguish the real data and the fake data generated by the generator as accurately as possible. During the training process, the generator and the discriminator play against each other, and the more realistic the data generated by the generator, the lower the accuracy of the discriminator. Through this adversarial training method, the generator and discriminator can continuously improve their performance, and eventually the generated fake data can be indistinguishable from the real data.GAN has a wide range of applications, including image generation, speech synthesis, natural language processing and other fields.

Figure 1 shows the model structure of GAN, G and D denote the generator model and discriminator model respectively, the input of G is the random variable z, the output of G is the generated samples x', and the training objective is to improve the similarity between the generated samples and the real samples to make D indistinguishable, i.e., to make the distribution of the generated samples (denoted as p_g) as identical as possible to the distribution of the real samples (denoted as p_{data}) distributions are as identical as possible. The input of D is either the real sample x or the generated sample x', and the output is the discriminative result. The training objective of D is to discriminate the real sample from the generated sample. The discriminative result is used to compute the objective function, and then the network weights are updated by backpropagation. In the process of adversarial training, D's ability to discriminate between true and false samples gradually improves, while G generates samples that gradually converge to true samples in order to deceive D, which ultimately leads to the generation of new data of better quality for the whole model.

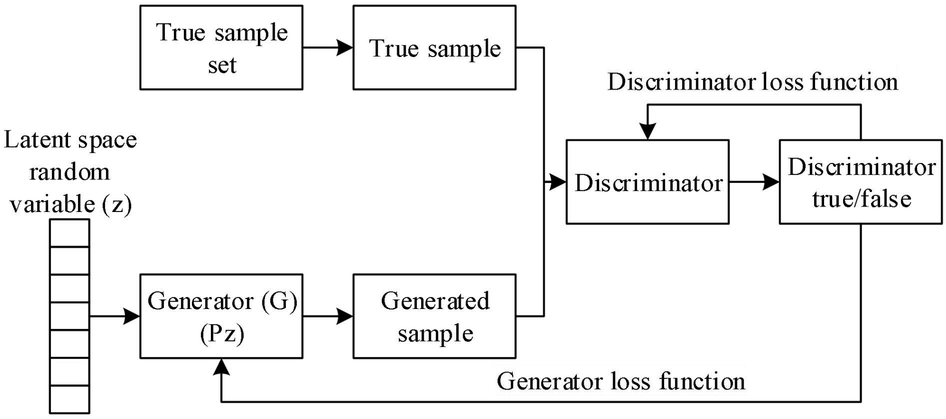


Figure 1. The framework of GAN model

The GAN training objective is to minimize the distance between p_g and p_{data} and maximize the accuracy of D to discriminate the samples, i.e., the value of $D(x)$ tends to 1 and the value of $D(x')$ tends to 0. The expression of the objective function is shown in Equation (4):

$$\min_G \max_D E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-D(G(z)))] \tag{4}$$

The adversarial training of GAN is carried out alternately by G and D, D is trained first, keeping G weights unchanged, selecting a batch of real vectors and hidden vectors both of size m, the generating samples are obtained from G by hidden variables, and then using the stochastic gradient ascent method to compute and update the weights of the D network by Equation (5); G is trained subsequently, a batch of generating samples are selected, keeping the D weights unchanged, and then utilize stochastic gradient descent method to compute and update the weights of G network via Eq. (6). When $p_g = p_{data}$, the global optimal solution is reached and the training is completed:

$$\nabla_{\theta_d} \frac{1}{m}\sum_{i=1}^{m}\left[\log D(x^i) + \log\left(1-D(G(z^i))\right)\right] \tag{5}$$

$$-\nabla_{\theta_g} \frac{1}{m}\sum_{i=1}^{m}\log\left(1-D(G(z^i))\right) \tag{6}$$

2.3. GAN-based collaborative filtering recommendation model design

Figure 2 shows the model framework diagram, the whole model consists of a generative model G and a discriminative model D, PR and NR denote the reconstruction loss of positive and negative items, respectively.

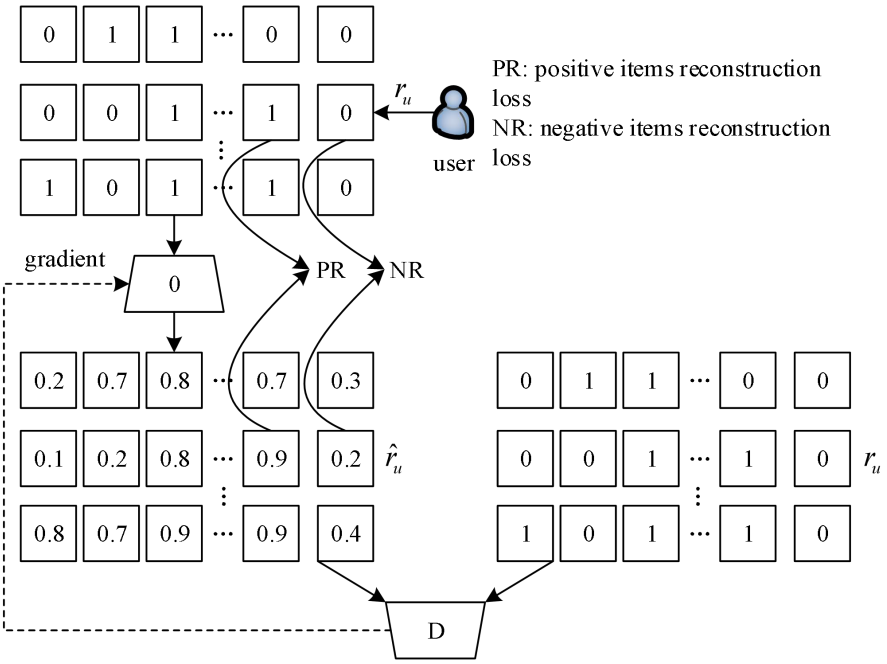


Figure 2. Model framework

First, assume two sets of m users and n items, which are represented in this chapter using $U = \{u_1, u_2, \ldots, u_m\}$ and $I = \{i_1, i_2, \ldots, i_n\}$. I_u denotes the set of items that user u has interacted with. The user item interaction information can be represented by a sparse matrix $R = (r_{ui})_{m \times n}$. The r_{ui} represents the interaction relationship between a user and an item, if user u has interacted with item i , i.e., $i \in I_u$ then $r_{ui} = 1$, otherwise $r_{ui} = 0$. For any given user u , this chapter uses r_u to denote his real interaction vector, which corresponds to the u th row vector in the user-item interaction matrix R , whose dimension is equal to the number of items n and the value of each dimension of the vector is binary, i.e., consists of only 0 or 1.

Given any user u , the generative model G captures the user's preference information by learning from existing user item interactions, and then generates a vector of the user's preferences for all items $\hat{r}_u$. The $\hat{r}_u$ is a n -dimensional dense vector, and the magnitude of the value of each dimension indicates the degree of the user's u preference for the item corresponding to the current location. The discriminative model D tries to distinguish between the real user interaction vector r_u and the generated user preference vector $\hat{r}_u$ and directs G to update the gradient. Through the game between D and G , D can effectively distinguish these two types of vectors, and G can also generate $\hat{r}_u$, which is very similar to r_u and contains the user's potential preference information, thus reaching the Nash equilibrium state..

Movement in the discriminant model D :

Denote its objective function by J^D with the expression:

$$J^D = l_D^{GAN} + \lambda reg(\phi) \tag{7}$$

In the above equation, l_D^{GAN} denotes the loss of D in GAN, ϕ is the parameter of D , $reg(\phi)$ is the loss of the L2 regular term of D , and λ is used to control the weight of the L2 regular term.

The goal of the discriminative model D is to maximize whether the vectors sent to D are from the true distribution or generated from the generative model G . The vectors pass through D and get a single-valued score, whose larger value indicates that the sample is trusted to a greater extent and has a higher probability of coming from the true distribution. The real user interaction vectors and the generated user preference vectors are spliced with their respective real interaction vectors r_u before they are fed into D , i.e., the inputs r_u and $\hat{r}_u$ are processed as $r_u \mid r_u$ and $\hat{r}_u \mid r_u$ denoting the process of vector splicing, which operates in such a way as to differentiate between different users, i.e., r_u and $\hat{r}_u$ in the current user condition. expressions can be obtained:

$$\begin{aligned} l_D^{GAN} &= E_{\hat{x}\sim P_{data}}\left(D(\hat{x})\right) - E_{x\sim P_\phi}\left(D(x)\right) \\ &= \sum\nolimits_u \left(D\left(\hat{r}_u \middle| r_u\right)\right) - \sum\nolimits_u \left(D\left(r_u \middle| r_u\right)\right) \\ &= \sum\nolimits_u \left(D\left(\hat{r}_u \middle| r_u\right) - D\left(r_u \middle| r_u\right)\right) \end{aligned} \tag{8}$$

where $D()$ is the score of the vector computed by the discriminant model. Here we use a multilayer feed-forward neural network to implement the discriminant model with an input dimension of $2\times n$ and an output dimension of 1 with the formula:

$$\begin{cases} y = \sigma_1\left(w_1 x + b_1\right) \\ y_k = \sigma_k\left(w_k y_{k-1} + b_k\right) \\ y_n = \sigma_n\left(w_n \cdot y_{n-1} + b_n\right) \end{cases} \tag{9}$$

where x is the input of the neural network, y_n is the output of the neural network, w_k , y_k , and b_k are the weights, inputs, and biases of the k th layer of the neural network, and σ_k is the activation function of the k th layer.

For the generative model G :

Denote its objective function by J^G with the expression:

$$J^G = l_G^{GAN} + l_R + \lambda reg(\theta) \tag{10}$$

In the above equation, l_G^{GAN} denotes the loss of G in GAN, l_R is the penalty term for the reconstruction loss corresponding to the positive and negative items, θ is the parameter of the generative model G , and $reg(\theta)$ is the G of the L2 regular term loss, and λ is used to control the weight of the L2 regular term.

G wishes to generate user preference vectors $\hat{r}_u$ that are sufficiently fake to deceive D and thus obtain high scores. Specifically, for each user u , G takes a high-dimensional sparse real interaction vector r_u as an input, and then tries to generate a realistic user preference vector $\hat{r}_u$. The $\hat{r}_u$ is a dense n -dimensional vector whose numerical magnitude in each dimension represents the user's u preference for the item corresponding to the current location. The G wants $\hat{r}_u$ to be as similar as possible to r_u , i.e., if $i \in I_u$, then the value of $\hat{r}_{ui}$ is as close to 1 as possible, and at the same time, $\hat{r}_u$ also fills in the value of the position where the value in r_u is 0 for prediction purposes. Like D , a multilayer feedforward neural network is used in this chapter to implement G , which captures the higher-order nonlinear interaction information of the user's items by means of a nonlinear activation function. The objective of G is opposite to that of D . When r_u is input into G , $\hat{r}_u$ is obtained. G hopes that the $\hat{r}_u$ it generates can obtain a high score through D . Therefore, the calculation method of its loss function in the GAN is exactly the opposite of that of D . In this chapter, l_G^{GAN} is used to represent the loss function of G in the GAN, and the expression is:

$$l_G^{GAN} = -\sum\nolimits_u D\left(\hat{r}_u \middle| r_u\right) \tag{11}$$

$D()$ denotes the score calculated by $\hat{r}_u$ through the discriminant model.

The model reaches the Nash equilibrium after adversarial training. In order that the generative model G can fully exploit the existing user item interaction information, we consider adding additional constraints to the generative model G so that the generated $\hat{\mathbf{r}}_{\mathbf{u}}$ reflects the user preferences more truly and accurately. Specifically, we add an additional penalty term l_R to the objective function of G , where $l_R = PR + NR$, to control the degree of deviation between the generated $\hat{r}_u$ and the actual r_u , with PR and NR representing the reconstruction loss for positive and negative items respectively.

During each iteration, we collect a portion of positive items $\left(i \in I_u\right)$ for each user u and put it into the used set $I - PR$. We use $S - PR$ to denote the proportion of positive items collected (e.g., if $S - PR = 4$, forty percent of the positive items from I_u are randomly collected and put into the set

$I-PR$). The PR constrains the generated user preference vector $\hat{r}_u$ to have a value as close to 1 as possible in the position of the corresponding positive item, and the expression for PR is:

$$PR = \alpha \cdot \sum_u \sum_i \left(x_{ui} - \hat{x}_{ui}\right)^2 \tag{12}$$

Among them, $\hat{x}_{ui}$ represents the value at the i th position in the vector $\hat{r}_u$, where i corresponds to the index of the positive item we have collected in the $I-PR$ set. where α is a variable parameter that controls the weight of the PR loss term.

Similarly, during each iteration, we collect a portion of negative items $\left(j \in I \setminus I_u\right)$ for each user u and put them into the set $I-NR$. We use $S-NR$ to denote the proportion of negative items in the collection. The NR constrains the generated user preference vector $\hat{r}_u$ to have a value as close to 0 as possible at the position corresponding to the negative item. i.e:

$$NR = \beta \cdot \sum_u \sum_j \left(x_{uj} - \hat{x}_{uj}\right)^2 \tag{13}$$

Among them, $\hat{x}_{uj}$ represents the value at the j th position in the vector $\hat{r}_u$, where j corresponds to the index of the negative examples we have collected in the $I-NR$ set. Here, β is a variable parameter used to control the weight of the NR loss term.

The final objective function of G is obtained as:

$$\begin{aligned} J^G = \sum_u \Big(& -D\left(\hat{r}_u \middle| r_u\right) + \alpha \cdot \sum_i \left(x_{ui} - \hat{x}_{ui}\right)^2 \\ & + \beta \cdot \sum_j \left(x_{uj} - \hat{x}_{uj}\right)^2 \Big) + \lambda reg(\theta) \end{aligned} \tag{14}$$

As mentioned earlier, this chapter uses a multilayer feedforward neural network to implement the generative model G and the discriminative model D with parameters θ and ϕ, respectively. In this chapter, the whole model is trained using a sparse user-item matrix and the objective functions J^G and J^D are optimized, and finally the parameters θ and ϕ are updated in the form of backpropagation. The update formula is obtained:

$$\begin{cases} \theta \leftarrow \theta - \mu_G \cdot \nabla_\theta J^G \\ \phi \leftarrow \phi - \mu_D \cdot \nabla_\phi J^G \end{cases} \tag{15}$$

In the above equation, $\nabla_\phi J^D$ and $\nabla_\theta J^G$ denote the gradient of J^D and J^G, respectively, μ_G and μ_D denote the learning rate of the generative model and discriminative model, respectively, and $\leftarrow$ denotes the assignment process.

3. Experimentation and evaluation

3.1. Experimental data and environment

The data for this experiment came from Shanghai X College, which provides students with online learning resources such as English Intercultural Teaching Movies, English Intercultural Teaching Post-Course Exercises, so that learners can interact with teachers through these online learning resources to achieve their learning objectives. The data included in this paper include the interaction time between users and online learning resources, the correct rate of users' after-class exercises, whether they have used hints or not, and teachers' feedback to users, etc. The interaction data of 2,500 users on 700 kinds of online learning resources, totaling 368,254 items, were included in this paper. In this experiment, the relevant data of 16600 users are randomly selected as the training set, and the rest of the users are used as the test set for offline experiments, and the method of testing adopts the method of cross-validation to judge the recommendation effect of the model.

This experiment is based on Windows 10 operating system, using Python language, and is conducted in PyCharm environment. The hyperparameter L of the deep neural network in the generator model and the discriminator model takes the value of 10.

3.2. Evaluation indicators

Assuming that only positive and negative samples exist in a model, the following definitions can be given:

True positives (TP): positive samples are correctly identified as positive samples.

True negatives (TN): negative samples are correctly identified as negative samples.

False positives (FP): false positive samples, i.e., negative samples are incorrectly recognized as positive samples.

False negatives (FN): false negative samples, i.e., positive samples are incorrectly recognized as negative samples.

Based on the above definition, the following evaluation metrics can be defined:

Precision rate:

$$\Pr ecision = \frac{tp}{tp + fp} = \frac{tp}{n} \tag{16}$$

Precision rate is actually the percentage of recognized samples that are correctly identified as positive.

Recall Rate:

$$Recall = \frac{tp}{tp + fn} \tag{17}$$

Recall is the proportion of all positive sample samples in the test set that are correctly recognized as positive.

If a classifier has a good performance, it should have a high recall value while the precision value remains high. A poorly performing classifier may lose a lot of precision rate values in exchange for an increase in the recall value.

We used hit rate, normalized discounted cumulative gain, precision rate, and recall rate as the evaluation metrics for this experiment.

The hit rate is defined as follows:

$$HR = \frac{1}{N}\sum_{i=1}^{N} hits(i) \tag{18}$$

where N denotes the total number of users and $hits(i)$ denotes whether the value accessed by the i th user is in the recommended list, 1 if it is and 0 otherwise.

The normalized discounted cumulative gain is defined as follows:

$$NDCG = \frac{1}{N}\sum_{i=1}^{N} \frac{1}{\log_2(p_i + 1)} \tag{19}$$

where N denotes the total number of users and p_i denotes the position of the real access value of the i th user in the recommendation list, or $p_i \to \infty$ if the value does not exist in the recommendation list.

3.3. Comparative experiments

UBCF: UBCF first uses statistical techniques to find neighbors with the same preferences as the target user, and then generates recommendations to the target user based on the preferences of the target user's neighbors. The basic principle is to use the similarity of users' access behavior to recommend the resources that users may be interested in to each other.

IBCF: IBC can discover the similarity between items and items based on all users' evaluations of items or information, and then recommend similar items to the user based on the user's historical preference information.

CB: CB is a widely used recommendation algorithm in industry. It discovers the relevance of an item or content based on its metadata and then recommends similar items to a user based on the user's previous preference history.

DNN: DNN can fit well to complex relationships in data by hierarchically performing nonlinear transformations through numerous simple linear transformations. In the field of recommendation, we can regard the recommendation system as a function of input feature data and output items to be recommended, and neural network is the fitting of this function. Currently, many studies have shown that neural networks have good performance in the recommendation field.

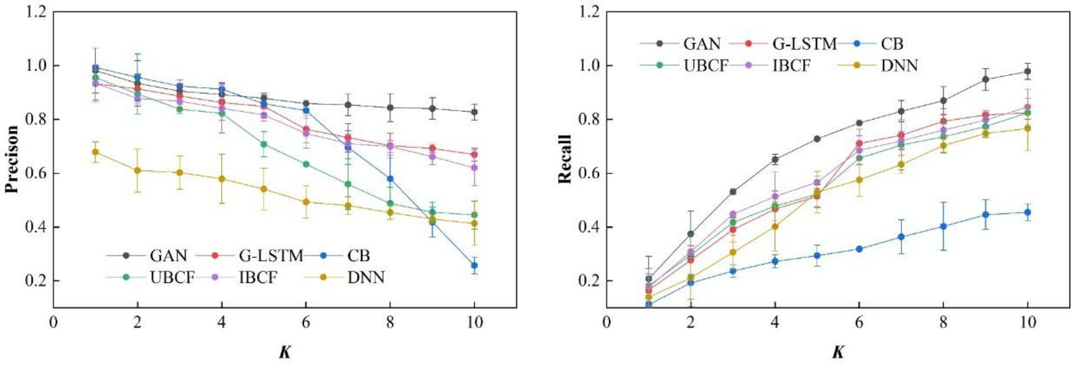
G-LSTM: G-LSTM solves the temporal problem and cold-start problem in online learning resources recommendation by integrating generalized matrix decomposition and long-short memory network, in which the long-short memory network module, which is good at dealing with temporal information data, is mainly used to extract the temporal information in the data of online learning resources, so as to solve the temporal problem of online learning resources recommendation, and the generalized matrix decomposition module can effectively capture the temporal information of online learning resources. The generalized matrix decomposition module can effectively capture the relationship between users and online learning resources in online learning resource data to alleviate the cold start problem.

3.4. Results and analysis

The main purpose of this experiment is to verify the recommendation ability of this model on real data, the parameter K indicates the number of learning resources recommended to the learner, and the value of parameter K in this experiment ranges from 1 to 10. The results of the precision rate and the recall rate of each recommendation method under different parameters K are shown in Fig. 3. It can be found that as K increases, the recall of our model can increase very fast, while the precision rate can be kept to decay at a slower rate.

It can be seen that when K takes a small value, the precision of the content-based recommendation and the generative adversarial network-based recommendation is very high; as K increases, the precision of the content-based recommendation and the generative adversarial network-based recommendation falls back, and it is still ahead of the other recommendation methods, but in terms of the recall rate, the content-based recommendation is very underperforming; when K goes to a large value, the precision rate and the recall rate of the content-based recommendation become very low, while the precision and recall of user-based collaborative filtering and item-based collaborative filtering remain at a respectable level, and the precision and recall of coordinated filtering recommendation of English intercultural teaching resources based on generative adversarial network leads all other recommendation models.

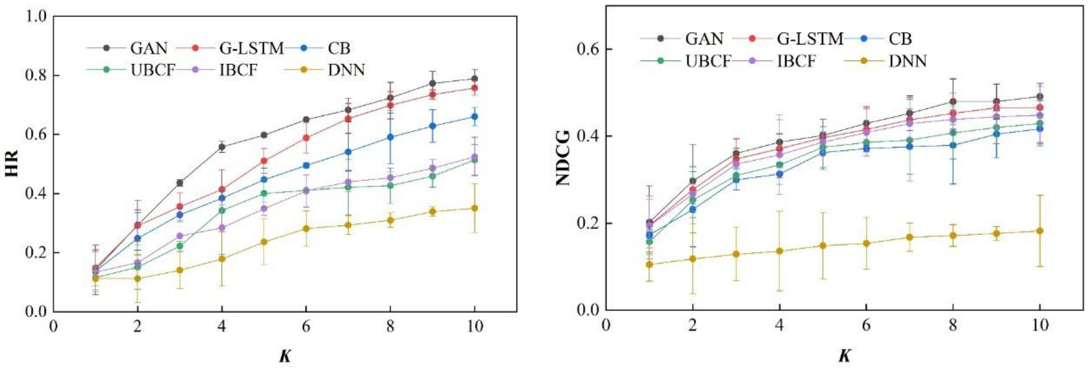
From the above results, it can be seen that the performance of neural network is very poor, this is because the sparseness of online learning resources data makes the neural network does not have enough data to make its training to fit the function of the recommendation system, and the characteristics of generative adversarial network can generate data to make up for the shortcomings of the insufficient amount of data to be used for training, so the recommendation system based on the generative adversarial network can have a very good performance. For content-based recommendation, as the recall rate increases, its accuracy decreases the fastest, this is because of the inherent shortcomings of the content-based recommendation itself, it can analyze the content is limited, feature extraction is more difficult to recommend to the user are some of the popular content, so although it can maintain a high accuracy rate, but this is achieved at the expense of a very low recall rate.



(a) Precision (b) Recall

Figure 3. Results of precision and recall

The results of hit rate and normalized discount gain for each learner under different parameters K are shown in Fig. 4. It can be seen that as K increases, the hit rate and normalized discount gain of each recommendation method are improved, when the value of K is small, the difference between the hit rate and normalized discount gain of each recommendation method is not obvious, but as K increases, the recommendation based on generative adversarial network is significantly better than other recommendation methods.



(a) HR (b) NDCG

Figure 4. Results of HR and NDCG

4. A Model of English Intercultural Communication Competence Cultivation Based on Concept Mapping and AI

The teaching model in this study is constructed on the basis of "the practicalization of teaching theory" and "the paradigm of teaching practice", and its systematic structure mainly consists of the following five elements: theoretical foundation, teaching objectives, operational procedures, realization conditions and evaluation.

(1) Theoretical foundation

The theoretical foundation of this study is Ausubel's "Meaningful Learning Theory", which is the basis for the construction of the teaching model under the conceptual mapping technology. The interaction between teachers and students visualizes the information in the process of English listening, speaking and translating, establishes the connection between new and old knowledge, and achieves meaningful learning, which is the point of relevance for this study to build a teaching model with concept mapping technology, and the interaction is the most prominent inherent feature of this teaching model. The second theoretical basis is the cognitive load theory, which may use various models of concept mapping to present information mainly in key words to replace the information presentation of complete syntax.

(2) Instructional Objectives

The goal of the personalized recommendation teaching model constructed in this study is set to solve the current problems in English listening, speaking and translation teaching to a certain extent, to release the students' potential for meaningful learning to the greatest extent possible in teaching practice, to practically improve their English application ability and linguistic thinking ability, and to gradually realize the goal of the new round of teaching reform, which focuses on improving college students' cross-cultural communication ability, and in this way leads to the improvement of other comprehensive abilities(interpretation). Interpretation).

(3) Operating Procedures

Operational procedures refer to the logical steps of teaching activities in time and the main practices of each step. The operating procedures in the teaching model are relatively stable, but not static. The concept map serves as an organizational scaffold in the instructional design session and as an interactive scaffold in the instructional implementation session.

(4) Realization conditions

It can be used as a curriculum and teaching design to express the teaching content and the knowledge system foundation necessary for teaching new knowledge in the teacher's mind in the form of visualization, so as to complete the curriculum and teaching preplanning with high quality and efficiency. It can promote knowledge assimilation and realize knowledge integration. With the support of recommendation algorithms, it triggers teaching interactions and realizes meaningful learning.

(5) Evaluation

Using concept maps as a tool for formative evaluation helps teachers emphasize students' experience in learning and communication between teachers and students. In teaching practice, we have found through classroom observation and student feedback that using concept maps as a formative assessment tool is conducive to promoting students' meaningful learning, cooperative learning and creative learning.

5. Empirical Evidence on the Cultivation of English Intercultural Communication Skills in Colleges and Universities

5.1. Empirical design

The experiment, using University L as a case study, consisted of a pre-experiment and a quasi-experiment. The pre-experiment randomly selected the Chinese language 1802 class as the experimental subject of the single-group pre- and post-test experimental design. The quasi-experiment randomly selected two classes of similar majors as the research subjects, and randomly chose Design 1902-05 as the experimental class and Animation 1902-03 as the control class to carry out the unequal group pre and post-test group comparison experiment. In order to test that the experimental sample attributes are representative of the overall attributes, 60 non-English majors were randomly selected from the 10 colleges of University L (in which there was an even proportion of men and women, arts and sciences, and grade spans) for the self-assessment test of English intercultural communicative competence level, and the mean value was obtained as 2.1. This was taken as the test value, and the mean value of the experimental subject's self-assessment of English language competence rating was subjected to a single-sample T test to check whether there is a significant difference between the sample mean and the overall mean. The results of the one-sample t-test show that: $t = 1.498$, $df = 0.188$, $p = 0.25 > 0.05$, i.e., there is no significant difference between the sample English intercultural communicative competence level water mean and the overall mean of the L-case school, which means that the sample is representative of the overall attributes.

This experiment takes intercultural communicative competence cultivation mode as the independent variable and college students' English intercultural communicative competence level as the dependent variable. The interfering factors were excluded by setting a control group whose characteristics and conditions were as identical as possible to those of the experimental group. Therefore, two natural classes with the same grade level, similar majors, similar learning experiences, the same teachers, the same English textbooks and the same classroom environment were chosen to participate in the experiment, and the experimental and control classes were randomly designated. After strictly controlling the irrelevant variables, the experimental treatment was implemented on the experimental classes to finally test the experimental hypotheses. The study takes natural classes as the experimental subjects, and adopts “English intercultural communication competence based on concept mapping and AI” in the experimental class, and adopts the traditional cultivation mode in the control class, with 30 students in each of the two classes.

Students in the experimental class can share their own works on the platform and view the works uploaded by other students and evaluate them. The students in the control class completed their concept maps and then passed the paper concept maps to each other in the class and evaluated them. For work analysis, a theme was selected from the concept maps submitted by the experimental class and the control class, and judged by both teachers according to the pre-designed category table.

5.2. Analysis of intercultural communication skills

(1) Independent samples t-test results of pre-test and post-test data

Independent samples t-test was conducted on the pre-test data, and the results of the pre-test independent samples t-test are shown in Table 1, which reveals that there is no significant difference between the data of the two classes. There is no significant difference between the experimental and control classes in the three dimensions of intercultural communication awareness, knowledge and competence, and the total score.

Table 1. Test results of the previous test

Dimension	Stage	N	Mean	SD	T
Consciousness	Experimental class	30	3.58	0.21	-0.88
	Control class	30	3.62	0.18	
Knowledge	Experimental class	30	3.88	0.25	0.77
	Control class	30	3.83	0.15	
Ability	Experimental class	30	3.73	0.26	0.61
	Control class	30	3.64	0.25	
Total score	Experimental class	30	11.19	0.33	0.38
	Control class	30	11.09	0.29	

After the end of the experiment, the post-test data of the two classes were subjected to independent samples t-test, and the results are shown in Table 2. In the dimension of intercultural communication awareness, t=0.55, p>0.05, there is no statistically significant difference between the experimental class and the control class; in the dimension of intercultural communication knowledge, t=3.12, p<0.01, there is a statistically significant difference between the experimental class and the control class; On the dimension of intercultural communicative competence, t=1.11, p>0.05, there is no statistically significant difference between the experimental class and the control class, and on the total score, t=2.12, p<0.05, there is a significant difference, with the experimental class having a higher mean score than the control class mean score by 0.41 points.

Table 2. The results of the independent sample t test were tested

Dimension	Stage	N	Mean	SD	T
Consciousness	Experimental class	30	3.81	0.26	0.55
	Control class	30	3.76	0.28	
Knowledge	Experimental class	30	4.22	0.22	3.12**
	Control class	30	3.95	0.29	
Ability	Experimental class	30	3.81	0.25	1.11
	Control class	30	3.72	0.33	
Total score	Experimental class	30	11.84	0.41	2.12*
	Control class	30	11.43	0.78	

(2) Paired-sample t-test results for pre and post-test data

Comparing the pre-test and post-test data of the two classes, it was found that there were differences between the post-test and pre-test in both classes respectively. The paired samples t-test was conducted on the pre and post-test data of each class, and the results of the paired samples t-test between the pre-test and post-test of the control class are shown in Table 3, and the results of the paired samples t-test between the pre-test and post-test of the experimental class are shown in Table 4. The difference between the changes in the control class before and after the experiment is not significant, while there is a significant difference between the pre-test and post-test of the experimental class in the dimensions of intercultural communication awareness, intercultural communication knowledge and the total scores, but there is no significant difference in the dimension of intercultural communication behavior.

Table 3. Test results of the comparison group and the posterior test pair

	Post-test	Pre-test	t
Consciousness	3.76±0.28	3.62±0.18	4.88**
Knowledge	3.95±0.29	3.83±0.15	4.15**
Ability	3.72±0.33	3.64±0.25	1.33
Total score	11.43±0.78	11.09±0.29	5.92**

Table 4. Test results of the matching sample of the test group

	Post-test	Pre-test	t
Consciousness	3.81±0.26	3.58±0.21	2.04
Knowledge	4.22±0.22	3.88±0.25	1.58
Ability	3.81±0.25	3.73±0.26	0.66
Total score	11.84±0.41	11.19±0.33	1.99

5.3. Content Analysis of Works

At the end of the experiment, the third assignment was selected for content analysis from the four assignments submitted by the students. This assignment was based on the theme of “Festive Cultures in English-speaking Countries-Christmas” because this theme was of great interest to the students, and the teacher spent the most time explaining this point during these festivals (Easter, Halloween, Christmas, etc.), so the students submitted more complete works. A total of 52 works were selected from the concept map works submitted by the two classes, of which 28 works were submitted by the experimental class, which were drawn using Mindjet Mindmanage, and 24 works were submitted by the control class, which were concept maps drawn on paper by the students. The number of nodes, effective frequency and node depth of these concept map works were content analyzed.

(1) Analysis of the number of nodes

The number of nodes in the concept map works was analyzed using the class table, and the level of the nodes was used as the basis for classification, i.e., nodes directly connected to the central concept Christmas Day were level 1 nodes, nodes connected to and subordinate to level 1 nodes were level 2 nodes, such as History, Food, etc. were level 2 nodes, and so on.

The results of the statistics of the number of nodes of all levels in the concept map works are shown in Table 5. After counting and accumulating the number of nodes of all levels in each concept map work, it is found that the total number of nodes of the concept maps of the students in the experimental class is 570, with an average of 20.36, while the total number of nodes of the concept maps of the students in the control class is 380, with an average of 15.83, and the difference between the averages of the two classes is 4.53. The number of concept map level 1 nodes of the students in the experimental class is 200 with a mean of 7.14 and the number of concept map level 1 nodes of the students in the control class is 160 with a mean of 6.67. The number of concept map level II nodes of the students in the experimental class is 300 with a mean of 10.71 and the number of concept map level II nodes of the students in the control class is 200 with a mean of 8.33, which is a difference of 28.57% between the two classes. The number of concept map level III nodes of the students in the experimental class is 50 with a mean of 1.79 and the number of concept map level III nodes of the students in the control class is 15 with a mean of 0.63. The number of level 4 nodes of the concept map of the students in the experimental class was 20 with a mean of 0.71 and the number of level 4 nodes of the concept map of the students in the control class was 5 with a mean of 0.21.

Table 5. Statistics on nodes at various levels in the concept diagram

Item	**Experimental work (28)**		**Control work (24)**		**Analysis**
	Total	**Mean**	**Total**	**Mean**	**Mean %**
Total node number	570	20.36	380	15.83	28.62%
Primary node number	200	7.14	160	6.67	7.05%
Secondary node number	300	10.71	200	8.33	28.57%
Three level node number	50	1.79	15	0.63	184.13%
Four level node number	20	0.71	5	0.21	238.1%
Cross node number	55	1.96	15	0.63	211.11%

(2) Effective frequency analysis of first-level nodes

The frequency analysis of the first-level nodes in the concept map works is carried out by using the class table, which is designed according to the content taught by the teacher and involves ten elements such as the history of Christmas, celebrations, food, symbols, etc. These ten elements are used as the standard to measure the validity of the content of the first-level nodes in each concept map work. These ten elements were used as a measure of the content validity of the first-level nodes, i.e., these ten elements were compared with the first-level nodes in each concept map work separately. The statistical results of the effective frequency of first-level nodes of content elements are shown in Table 6. From the statistical data, it is easy to see that the average effective frequency of each element of the first-level nodes of the concept maps of the students in the experimental class is 19.5, accounting for 69.64% of the total frequency, and the average effective frequency of each element of the first-level nodes of the concept maps of the students in the control class is 15.8, accounting for 65.83% of the total frequency; the average effective frequency of the nodes in the experimental class is higher than that of the control class by nearly 4 percentage points. In terms of each element, the effective frequencies of the two classes on the elements of Greeting, Drink and Song are basically equal; the effective frequencies of the first-level nodes of the concept maps of the students in the experimental class on the elements of Activity, Gift, History, Plants and Symbol are higher than those of the students in the control class, and those of the concept maps of the students in the control class on the elements of Color and Food elements have higher effective frequencies than the students in the experimental class.

Table 5. The effective frequency of the primary node is the statistical result

Topic	Experimental work (28)		Control work (24)	
	Frequency	Percentage	Frequency	Percentage
Activity	17	60.71%	10	41.67%
Color	20	71.43%	19	79.17%
Drink	18	64.29%	16	66.67%
Food	16	57.14%	15	62.50%
Gift	25	89.29%	17	70.83%
Greeting	25	89.29%	23	83.33%
History	20	71.43%	15	62.5%
Plants	18	64.29%	18	75.00%
Song	19	67.86%	14	58.33%
Symbol	17	60.71%	11	45.83%
Total effective frequency	195	69.64%	158	65.83%
Average effective frequency	19.5	69.64%	15.8	65.83%

(3) Node depth analysis

The total number of nodes at each level was counted, and the total value and the average value of the node depth of the concept map works of the experimental and control classes were calculated separately. The total and average values of the node depth of the conceptual graph works of the two classes are shown in Table 7, which shows that the average depth of the conceptual graphs of the students in the experimental class is 1.81, and the average depth of the conceptual graphs of the students in the control class is 1.57, and the difference between the two classes is 0.24.

Table 7. The mean of the total value of the project's node depth

	Experimental class	Control class
ND1	200	160
ND2	598	394
ND3	156	28
ND4	75	15
Total depth value	1029	597
Total node number	570	380
Mean depth	1.81	1.57

6. Conclusion

With the increasing sophistication of the level of science and technology as well as network technology, the network coverage has become more and more extensive, which provides great convenience for people's life. In this paper, we propose a GAN-based collaborative filtering cross-cultural teaching resources recommendation model for English in colleges and universities and combine it with conceptual maps to realize the cultivation of cross-cultural communicative competence in English.

Teaching resource recommendation experiments were conducted, and we used precision rate, recall rate, hit rate with normalized discounted cumulative gain as evaluation indexes, and compared the recommendation results with those of user-based collaborative filtering, item-based collaborative filtering, content-based recommendation, deep neural network-based recommendation, and G-LSTM-based recommender system, respectively, and the results showed that the method based on Generative Adversarial Networks is better than other methods.

Conducting the practice of cultivating intercultural communicative competence in English, there are significant differences between the pre and post-tests of the experimental class in the dimensions of intercultural communicative awareness, intercultural communicative knowledge and the total scores, but there is no significant difference in the dimension of intercultural communicative behavior. The use of software concept maps facilitates sharing, cooperation, exploration, and evaluation among students, and has a better effect than paper-and-pencil concept maps in promoting students' intercultural knowledge, which to a certain extent can promote deeper development of students' cognitive thinking.

In this paper, when extracting user and learning resource features, it is necessary to manually construct the extraction, and the construction of features cannot be completed automatically. If the features are not properly constructed, the effect of the model will be greatly reduced, therefore, in the next step of research work, the automated extraction of user and learning resource features will be studied.

Funding

This paper is the research output of the following projects:

1. The 2025 Higher Education Research Project of the 14th Five-Year Plan of the Guangdong Society of Higher Education: Research on the Tripartite Collaborative Guidance of "Teaching, Competition and Research" to Improve the Applied Competence of Undergraduate Foreign Language Talents under the Background of Digital Transformation (No. 25GYB107);
2. The 2025 Youth Project of the China Association for Non-Government Education: Research on the Tripartite Collaboration of "Teaching, Competition and Research" to Improve the Applied Competence of Foreign Language Talents in Private Universities under Digital Transformation (No. CANQN250363);
3. The 2024 Construction Project of the Undergraduate University Teaching Quality and Teaching Reform Project of Guangdong Province: Comprehensive Business English Course Teaching and Research Office (No. 2024-309), sponsored by the Department of Education of Guangdong Province;
4. The 2025 University-Level Higher Education Teaching Reform Project of Guangdong Technology College: AI-Enabled Teaching Reform of Foreign Language Competitions and Construction of a Training System (No. JXGG2025087).

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