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Research on the Innovation and Practice of English Speaking Training Mode in Digital Education Environment

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SUMMARY: *With the development of English education and teaching, the use of digital technology in oral classroom teaching has been emphasized. In this paper, digitalization empowers English speaking training and explores the innovative mode of English speaking training. Based on the application of teaching platform and differentiated teaching needs therein, the English speaking learning system based on personalized needs is proposed, and a personalized resource recommendation model is constructed through the combination of student interest feature extraction and collaborative filtering recommendation algorithm. Then it carries out the teaching practice of students in four business English major classes in a school. From the experiment, it is evident that this system offers a higher accuracy and faster resource recommendation to the experimental group compared to the other system with an accuracy of more than 90% and a recommendation time decrease of 79.51% and 72.50%, respectively. The improvement of students' oral performance and oral expression time in the experimental group were 9.82%~15.09% and 150.21%~176.05%, respectively, and the class with this paper's system had the best performance among the three classes. The English speaking training model based on digitization can promote students' willingness to express English and the length of expression, and enhance students' English speaking learning effect.*

KEYWORDS: *digitalization; collaborative filtering algorithm; personalized recommendation; teaching practice; spoken English*

1 Introduction

With the development of information technology, digital means have penetrated into all aspects of education, many schools have realized digital teaching, and education technology is developing in the direction of intelligence, personalization and interaction [1, 2]. The integration of artificial intelligence, big data, cloud computing and other technologies has made educational resources more colorful and teaching methods more flexible and diverse. Online learning platforms, intelligent teaching assistants, virtual reality and other technologies are widely used in the field of education, providing learners with a broader learning space.

In such a background, the English speaking training mode has ushered in unprecedented opportunities. The development of digital education makes English speaking training no longer subject to geographical and time constraints, and learners can learn anytime and anywhere through online platforms [3]. At the same time, the application of intelligent

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teaching assistants can provide personalized learning solutions according to learners' characteristics and needs, helping learners improve their speaking skills more efficiently [4, 5]. Regarding the personalized learning brought by digitalization, Zhai [6] designed an English speaking learning system based on cloud computing, which can realize the learning of English speaking knowledge, simulation of English speaking test's, etc., and can provide personalized learning solutions according to the students' learning situation to improve their English speaking level. Jitpaisarnwattana [7] investigated how the use of personalized learning plans (PLPs) in LMOOCs would impact the oral ability development of English language learners and discovered that PLPs significantly improve learners' oral abilities and have a positive effect on the English language learning process as a whole. Hashim and Shaher [8] attempted to evaluate the role of AI in English language teaching within a digitally disembodied environment, and their study showed that AI creates valuable opportunities for personalized English language education, not only by strengthening students’ language abilities, but also by offering an individualized language learning experience.

In addition, digital education creates more authentic contexts and interactive settings for English speaking training. With the support of virtual reality technology, learners are able to engage in oral practice within simulated environments so as to improve the fluency and accuracy of spoken production [9, 10]. Real-time interactive functions on online learning platforms, such as online dialogues and group discussions, also provide learners with more opportunities for practice and support the development of oral communication competence [11, 12]. Shi et al [13] explored how immersive virtual reality (iVR) is applied to students’ English speaking ability and participation, and, based on comparative experiments and survey analyses, concluded that iVR can improve students’ skills in grammar, vocabulary, pronunciation, and interactive communication. Zheng [14] investigated the effects of contemporary technologies on English language instruction, concentrating in particular on the use of virtual reality technology, educational software, and online learning environments. The study demonstrated that the use of contemporary technologies offers learners better English language learning, personalized learning experiences, and immersion. However, Shadiev et al [15] investigated the application of 360-degree video-powered immersive virtual reality settings to English language acquisition. They demonstrated that immersive 360-degree virtual worlds have an impact on vocabulary learning and reduce speaking anxiety based on their literature evaluation. Li et al [16] explored the influence of augmented reality on English language learning and assessed it through semi-structured in-depth interviews. The results suggested that the digital immersive language learning experience enabled by augmented reality can effectively enhance English language learning.

Furthermore, digital education also supplies abundant teaching resources for English speaking instruction. Learners can obtain a wide range of English learning materials through online platforms, including listening resources, speaking strategy guides, English videos, and other materials, which can help them broaden their horizons and strengthen their interest in oral training [17-20].

Through the adoption of digital methods, this research examines an innovative method of teaching spoken English in terms of building authentic situations, widening the oral learning environment, adopting differentiated instruction, and performing varied assessments. In order to better facilitate the widening of oral learning environments and differentiated instruction, personalized recommendation technology is adopted in the area of online learning, and an English speaking learning platform is designed based on personalization and personalized recommendation according to interest preferences, thereby realizing personalized recommendation. Subsequently, the students who are studying Business English at a specific educational institution in 2023 are chosen as experimental subjects, and the personalized recommendation platform and English speaking training model designed in this paper are tested by analyzing the recommendation accuracy and recommendation time of the learning resources as well as the comparison between the speaking scores and speaking output length of four classes before and after the experiment.

2 Innovations in oral English training models

With the growth of information technology and the speed of educational modernization, digital tools have become a significant way by which teachers can enhance the effectiveness of English speaking classes. In this chapter, a new model for English speaking training under the context of digitalized education will be proposed. The English speaking training model based on digitalization is illustrated in Figure 1. It comprises four components.

Figure 1: A digital English speaking training model

2.1 Create authentic contexts

Create real contexts to strengthen students' speaking practice. Creating contexts close to real life for students to carry out oral training, this kind of practical learning makes students feel the charm and practicability of the language, thus enhancing their willingness to learn spoken English. Teachers can combine the content of the textbook and students' interests to design contexts close to life and guide students to carry out speaking practice in real contexts. In the process of practicing, teachers should encourage students to express themselves boldly, and at the same time give timely feedback and correction to students' oral expression to help them improve their pronunciation and expression.

2.2 Expanding the oral learning space

Expanding students' oral learning space by means of information technology. Information technology expands students' practicing space by providing online platforms, virtual scenarios and diversified learning resources. Teachers can use online teaching platforms to set training tasks for students, complete task evaluation and push practice resources in a targeted way.

With the help of information technology, teachers can guide students to carry out oral practice anytime and anywhere, creating a free oral practice environment for students.

2.3 Implement differentiated instruction

As students' English learning abilities are strong or weak, and their oral expression levels are also different, teachers should adopt appropriate teaching methods for students at different levels in order to better help students improve their oral skills. Teachers can comprehensively assess students' language proficiency, such as vocabulary, grammatical accuracy and learning styles, through pre-class speaking tests, classroom observations and student self-assessment scales, or utilize intelligent digital platforms to tap into students' learning interests. Based on this, teachers should design hierarchical tasks: for weak students, assign templated fill-in-the-blank exercises to reinforce students' memorization and use of relevant sentences and vocabulary. For more capable students, they can arrange open-ended discussions to further practice their language organization and expression skills. At the same time, teachers can meet students' individual needs through individual tutoring, such as 10-minute targeted pronunciation correction after class.

2.4 Conducting diversified evaluations

Adopting diversified evaluation methods, such as students' self-assessment, mutual assessment and teachers' evaluation, to comprehensively evaluate students' oral performance can stimulate students' motivation and self-confidence in oral learning. In the evaluation, the teacher focuses on scoring in terms of logic, vocabulary diversity and other dimensions. Students focus on self-assessment in terms of language intonation and content integrity. Peer evaluation focuses on evaluating each other's strengths and weaknesses and making suggestions for improvement. At the same time, the teacher should transform the evaluation results into a visual report to help students clarify the direction of improvement.

3 Personalized needs-based system for learning spoken English

3.1 Overall Architecture Design

A personalized needs-based oral English learning system is proposed based on the recommended model of oral English training in order to better accomplish practice resource push and differentiated instruction. Fig. 2 shows the system's overall design structure. The system may be broadly divided into four modules: resources and database, teacher resource management, learner learning, and personalized suggestion.

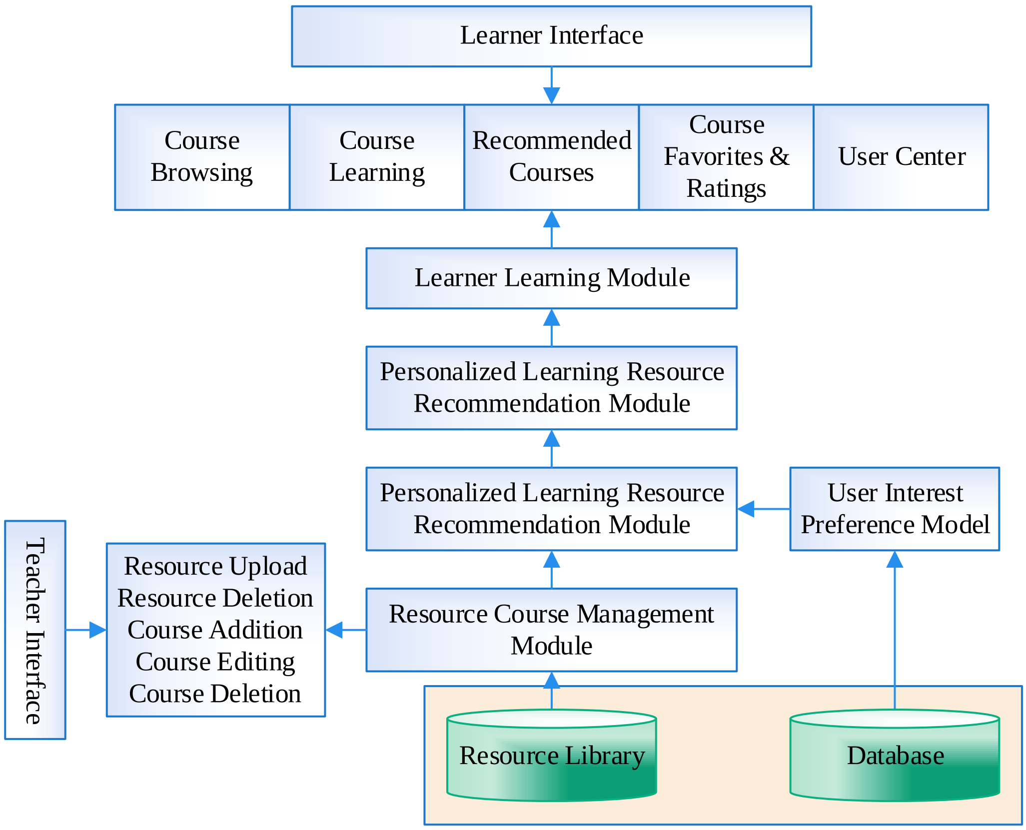

Figure 2: The overall design framework of the system

3.2 Personalized Resource Recommendation Method

Personalized resource recommendation serves as the core component of the system. To achieve individualized recommendation of English speaking learning materials, this paper improves the conventional user-based collaborative filtering algorithm and proposes a collaborative filtering recommendation approach grounded in students' interests and preferences.

3.2.1 Collaborative Filtering Recommendation Algorithms

However, the critical factor of the UserCF model is the computation of the similarity among the users. The model is initially fed the users' past relationships, after which the similarity formula is used to determine how similar the target user is to other users. Users with strong similarity scores are then utilized as the target user's closest neighbors. The rating of the nearby users is used to predict the target user's rating score on the project. Finally, N projects are suggested to the target user depending on the target user's anticipated interest in the project.

(1) User rating matrix

The degree of a user's interest in a certain project may be determined by their ratings. Given that there are m users and n projects, the historical data on user ratings can be recorded in a m × n matrix, where each value in the matrix represents a user's rating for a specific project, and rows represent individual users and columns represent individual projects.

(2) Similarity calculation method

Similarity computation constitutes the core of collaborative filtering technology, and the way similarity is measured can, to some extent, affect the recommendation performance of collaborative filtering algorithms. Euclidean distance, the Jaccard coefficient, cosine similarity, modified cosine similarity, and the Pearson correlation coefficient are examples of common similarity metrics.

In recommender systems, each user's ratings across all items may be viewed as an n-dimensional vector, that is, as a point in n-dimensional space. The Euclidean distance between two points can then be used to assess the similarity between users. The formula for Euclidean distance is given as follows:

$$sim(u,v)=\sqrt{\sum_{i\in I}\left(R_{ui}-R_{vi}\right)^2} \tag{1}$$

where $sim(u,v)$ denotes the similarity of users u and v, I denotes the set of items, and R_{ui} and R_{vi} denote the ratings of users u and v on item i.

Instead of concentrating on the individual rating values of users, the Jaccard similarity coefficient considers the quantity of rating items that users share. Formula for calculation:

$$sim(u,v)=\frac{\left|I_u \cap I_v\right|}{\left|I_u \cup I_v\right|} \tag{2}$$

where $sim(u,v)$ denotes the similarity of users u and v, and I_u and I_v denote the set of items that users u and v have rated.

The vectors of user rating preferences for all objects could be considered as n-dimensional vectors where each user preference for one object could be viewed as a component of that vector. The Euclidean distance between two vectors could be applied for evaluating user similarity based on the following equation:

$$sim(u,v)=\frac{\vec{u}*\vec{v}}{\left|\vec{u}\right|*\left|\vec{v}\right|} \tag{3}$$

where $sim(u,v)$ denotes the similarity of users u and v, and $\vec{u}$ and $\vec{v}$ denote the vectors of ratings of users u and v for all items, respectively. The larger the cosine value, the more similar the users are.

Corrected cosine similarity measures the cosine by taking into account the mean rating values of the users, thus eliminating any effects of scoring behavior of the users. Calculation formula:

$$sim(u,v)=\frac{\sum_{i\in I}\left(R_{ui}-\bar{R}_u\right)\left(R_{vi}-\bar{R}_v\right)}{\sqrt{\sum_{i\in I}\left(R_{ui}-\bar{R}_u\right)^2}*\sqrt{\sum_{i\in I}\left(R_{vi}-\bar{R}_v\right)^2}} \tag{4}$$

where $sim(u,v)$ denotes the similarity of user u and user v, I denotes the set of items, R_{ui} and R_{vi} denote the ratings of user u and v on item i, respectively, and $\bar{R}_u$ and $\bar{R}_v$ denote the ratings of user u and v on the average of all item ratings.

Pearson's Correlation Coefficient is used to determine the relationship between two variables. It falls within the range of −1 and 1. If the value of the correlation coefficient is positive, there exists a direct relationship between the two variables, while a negative value suggests an inverse relationship. In recommendation systems, the rating given by a user for an item can be considered as one variable, and the correlation coefficient between such variables, considering only those items rated by users, will indicate user similarity. This can be calculated using the formula below:

$$sim(u,v)=\frac{\sum_{i\in I_{uv}}\left(R_{ui}-\bar{R}_u\right)\left(R_{vi}-\bar{R}_v\right)}{\sqrt{\sum_{i\in I_{uv}}\left(R_{ui}-\bar{R}_u\right)^2}*\sqrt{\sum_{i\in I_{uv}}\left(R_{vi}-\bar{R}_v\right)^2}} \tag{5}$$

where $sim(u,v)$ denotes the similarity of users u and v, I_{uv} denotes the set of items rated by both users u and v (i.e., jointly rated items), R_{ui} and R_{vi} denote the ratings of users u and v on item i, respectively, and $\bar{R}_u$ and $\bar{R}_v$ denote the mean of user v and u's ratings for all items, respectively.

The $\bar{R}_u$ and $\bar{R}_v$ formulas:

$$\bar{R}_u=\frac{1}{\left|I_{uv}\right|}\sum_{i\in I_{uv}}R_{ui},\bar{R}_v=\frac{1}{\left|I_{uv}\right|}\sum_{i\in I_{uv}}R_{vi} \tag{6}$$

(3) Rating Prediction

We employ the previously mentioned formula to calculate user similarity under the UserCF Algorithm. The nearest neighborhood set is then determined by applying the top-N users who are closest to the target user. We then use the following equation to forecast the rating of those goods that the target user has not evaluated by applying the rating of nearest neighbors:

$$\hat{R}_{ui}=\bar{R}_u+\frac{\sum_{v\in N_u}sim(u,v)*\left(R_{vi}-\bar{R}_v\right)}{\sum_{v\in N_u}\left|sim(u,v)\right|} \tag{7}$$

where $\hat{R}_{ui}$ denotes the predicted rating of user u on item i, $\bar{R}_u$ and $\bar{R}_v$ denote the mean value of user u's and v's ratings on all items, respectively, $sim(u,v)$ denotes the similarity between user u and user v, and N_u denotes the set of neighbors consisting of N users with the highest similarity to the target user u.

3.2.2 Student interest feature extraction

To better satisfy students' personalized spoken-English learning needs and achieve personalized recommendation, this paper collects users' attribute features, behavioral features, and learning features in terms of cognitive level and learning preference.

User Attribute Characteristics: In this system, the attribute features mainly collected for students include the grade they are in and the labels of their areas of interest.

User Behavioral Characteristics: Behavioral data are mainly collected from the number of course clicks, the duration of stay on course pages, and records of favorite selections.

User Learning Characteristics: The learning records of students are collected, including the names of the courses they have studied, the ratings of the course resources, the grades and subjects to which the courses belong, and the teachers who taught the courses.

After acquiring these data, it is also necessary to perform feature calculation to get the user's preference characteristics, and then build an interest preference model based on these data.

(1) Resource preference

Favorites, where 0 denotes the lack of favorites and 1 indicates they have been favored, will reflect more on the interest preferences of users than the two. Students' click rate and time spent can respond to interest preferences from a particular perspective. Formula for calculation:

$$\text{User Course Preference} = \frac{\text{Current Clicks}}{\text{Total Course Clicks}} + \frac{\text{Dwell Time}}{\text{Total Course Dwell Time}} + (0 or 1) \tag{8}$$

(2) Student Knowledge Scope

User Knowledge Scope Degree is an indication of the stage and range of ability at which the user's current level of knowledge is located, $grade$ indicates the level of the current course, n indicates the number of pieces of knowledge to be learned at this level, and l indicates the total number of courses to be learned. Calculation formula:

$$\text{User Knowledge Scope} = \frac{\text{grand } \cdot n}{l} \tag{9}$$

(3) Teacher preference

Teacher denotes a particular teacher, n denotes the number of times the teacher's courses were taken, and l denotes the total number of courses taken. Calculation formula:

$$\text{User Interest in Teachers} = \frac{\text{Teacher } \cdot n}{l} \tag{10}$$

3.2.3 Modeling student interest preferences

The student interest preference model consists of two main types of features: attribute features and learning features. Attribute features are: grade level, interest label. Learning characteristics are: resource preference, learning scope preference, teacher preference. The interest preference values are obtained through the above formula, and the preference values of each category are ranked in descending order, and the first 8 items with higher preference are selected as the display items of the preference features, and all items with less than 8 items are taken as the preference items.

3.2.4 Calculating similar neighbors

In this research, two different neighbor calculation methods are used together – the interest preference model-based method to select neighbors using the interest preferences of students, and the learning record-based method to select neighbors based on learning records of students.

(1) Similarity calculation based on the student interest preference model

(a) Similarity of users' knowledge level

Define the similarity of the knowledge level of user a and user b to be denoted by $S(a,b)$, when the two users have the same level of knowledge range $S(a,b)=1$. When the two users' knowledge range levels do not agree $S(a,b)=0$. Where S_a denotes the knowledge competence level of user a and S_b denotes the competence level of user b, the similarity $S(a,b)$ between the knowledge level of user a and user b:

$$S(a,b)=\begin{cases}1, & S_a = S_b \\ 0, & S_a \neq S_b\end{cases} \tag{11}$$

(b) Interest label similarity

Define the similarity of interest tags of user a and user b is denoted by $I(a,b)$, the set of interest tags of user a is $I_a=\{I_{a1},I_{a2},I_{a3}\cdots I_{am}\}$, and the set of interest tags of user b is $I_b=\{I_{b1},I_{b2},I_{b3}\cdots I_{bn}\}$, where the value of the same number of tags is k, then the similarity of interest tags of user a and user b is $I(a,b)$:

$$I(a,b)=\frac{k}{m+n-k} \tag{12}$$

(c) Resource preference similarity

Define the similarity of resource preferences of user a and user b as denoted by $J(a,b)$, the set of preferred courses of user a as $J_a=\{J_{a1},J_{a2}\cdots J_{am}\}$, and the set of preferred resources of user b as $J_b=\{J_{b1},J_{b2}\cdots J_{bn}\}$, where the value of the number of the same individual resources is h, then the similarity of resource preferences of user a and user b is $J(a,b)$:

$$J(a,b)=\frac{h}{m+n-h} \tag{13}$$

(d) Learning range preference similarity

Define the learning range similarity of user a and user b to be denoted by $L(a,b)$, the learning range set $L_a=\{L_{a1},L_{a2}\cdots L_{am}\}$ for user a, and the learning range preference set for user b as $L_b=\{L_{b1},L_{b2}\cdots L_{bn}\}$, where the same range value is r, the course preference similarity $L(a,b)$ between user a and user b:

$$L(a,b)=\frac{r}{m+n-r} \tag{14}$$

Similarly, the user preference similarity for teachers is calculated by the same principle as above, defining the user teacher preference similarity value as $D(a,b)$, then the user similarity based on the user interest preference model $Sim(a,b)$:

$$sim(a,b)_{\mathrm{mod}el}=\alpha S(a,b)+\beta I(a,b)+\theta J(a,b)+vL(a,b)+\mu D(a,b) \tag{15}$$

In the formula, α, β, θ, v, μ are the weight factors, and $\alpha+\beta+\theta+v+\mu=1$, representing the proportion of the weight of each sub-item in the whole similarity, the larger the weight value indicates that the item has a greater impact on the similarity between users.

(2) Specific calculation based on user resource rating items

Step1: Assuming that the user rating data contains m user sets and n items, the "user-rating" matrix is generated based on the students' learning records, and $V(m,n)$ denotes the ratings of the resources.

Step2: Construct a "learning resource-user" data structure to obtain the set of neighbors of users who have studied the same learning resource.

Step3: Based on the common scoring learning resource, the modified cosine similarity algorithm is used to calculate the similarity value between users, $sim(i,j)$ represents the similarity value between user i and user j, k represents the common scoring learning resource, $\bar{R}_i'$ and $\bar{R}_j'$ represent the mean value of user i and with user j's ratings in the co-scoring program, and the calculation formula:

$$\begin{aligned} sim(i,j)_{score} &= \cos(\vec{i},\vec{j}) = \frac{\vec{i}\cdot\vec{j}}{\left|\vec{i}\right|\times\left|\vec{j}\right|} \\ &= \frac{\sum_{k\in y_{ij}}\left(R_{i,k}-\bar{R}_i'\right)\left(R_{j,k}-\bar{R}_j'\right)}{\sqrt{\sum_{k\in M_i}\left(R_{i,k}-\bar{R}_i'\right)^2}\sqrt{\sum_{k\in y_{ij}}\left(R_{j,k}-\bar{R}_j'\right)^2}} \end{aligned} \tag{16}$$

Finally, the resultant values of the two computational methods are summed, and the rule of the operation is to superimpose the two similarity values of the same user. Define the final similarity of users is denoted by $sim(i,j)_{final}$ and λ is the weight factor, then:

$$sim(i,j)_{final} = \lambda sim(i,j)_{\mathrm{mod}el} + (1-\lambda)sim(i,j)_{score} \tag{17}$$

After calculating the results, $sim(i,j)_{final}$ is size-ordered, and the top N items are selected as sub-items of the nearest-neighbor user set in descending order, and finally recommendations are made based on the predicted scores of the nearest-neighbor items.

3.2.5 Generating recommendations

Using the extended neighbor set generated based on the interests of the user and the direct neighbors based on their assessment of the resources, the current research predicts the scores of those resources which have not been either utilized by the target user or assessed by him, and selects the top N resources with the highest score predictions as the recommendations for the user.

$$P_{u,i} = \bar{R}_u + \frac{\sum_{v\in s(u)}\left(R_{v,i}-\bar{R}_v\right)\cdot sim(u,v)}{\sum_{v\in s(u)}\left|sim(u,v)\right|} \tag{18}$$

Here, $P(u,i)$ denotes the predicted score of user u on unrated item i, $s(u)$ denotes the set of similar neighboring users of user u, $\bar{R}_u$ denotes the average score of the rated items of user u, and $\bar{R}_v$ denotes the average score of the rating items of neighboring user

v.

4 Practical research on oral English training

4.1 Study design

4.1.1 Research questions

On the basis of the proposed oral English training model and the personalized oral English learning system, this study investigates the effect of the learning resource recommendation function within the system and further explores whether this training model can enhance students' willingness to engage in spoken English expression and extend the length of their oral output, thereby producing better teaching outcomes.

4.1.2 Objects of study

A total of 160 students from four Business English classes at a certain institution in 2023 were chosen as the study's subjects. Prior to the start of this study, there was no difference in the English speaking abilities of the students in these four courses based on the oral proficiency test results. Of these 160 students, 40 students in Class 4 made up the control group, which received instruction using the conventional technique, and 120 students in Classes 1-3 made up the experimental group, which followed the English speaking training methodology suggested in this work. The trial ran for eighteen weeks in total.

The intelligent teaching system based on deep learning and the online open course system based on B/S architecture are two other types of learning systems that are compared to the newly developed system in order to demonstrate the effectiveness and superiority of the research on the English speaking learning system based on the needs of each student. Therefore, Class 1, Class 2, and Class 3 are the three courses that use the English speaking training paradigm suggested in this work.

4.1.3 Specific operations

The four groups of students were tested on their English speaking level before the experiment to determine their speaking level. The two groups of students were tested again in the later part of the experiment to compare the changes in their speaking levels.

Teaching implementation:

(1) The form of the speaking teaching activities in the regular groups is the traditional task-based learning mode. The teacher demonstrates the necessary language knowledge and skills through real-life situations, and then assigns communicative tasks, in which students simulate participating in interviews, telemarketing, business meetings, business trips, etc., and have conversations or answer questions in English. The teacher assessed the task completion after the activity.

(2) The experimental group teaches in the English speaking training mode, i.e., creating authentic contexts for speaking training in the classroom, using the learning system to push learning resources and training tasks, implementing differentiated teaching, and carrying out diversified evaluations to stimulate students' motivation for oral learning and improvement of oral ability.

(3) Testing and scoring. Take the speaking test of the control group and the experimental group as the topic speech. Teachers select 5 real problems, each student randomly selects 1 problem, prepares for 5 minutes, prepares a speech of about 1~2 minutes to elaborate his/her own solution. 4 classes are tested by two teachers at the same time, and the test is carried out

in two times, each time 20 students are tested, completed in one week, and the test is video-recorded in its entirety. The test was videotaped and graded by all three teachers. The scoring criteria mainly include five indicators, namely, the degree of deduction of the speech content, the length of the speech, the clarity of organization, the fluency of expression and the degree of grammatical accuracy, with a full score of 100 points.

(4) Test of learning system. Investigate the needs of students in classes 1~3 for different oral English learning resources, and count the recommendation results and recommendation time of the learning system, and measure the recommendation accuracy and recommendation efficiency of the learning system.

4.1.4 Data analysis

Scores and presentation times for each of these groups were ascertained by counting and analyzing the results of the two oral examinations administered prior to and following the experiment. For the three classes of students in the experimental groups, it was also determined how many suggestions were effective and how long each recommendation took.

4.2 Analysis of experimental results

4.2.1 Learning system performance

The assumption here is that the experimental students will have the highest need for the following learning resources: spoken English vocabulary learning resource, spoken English sentence learning resource, pronunciation practice learning resource, spoken English grammar learning resource, creative expression learning resource, and scene dialog learning resource, and their actual needs will be as indicated in Table 1 below.

Table 1: The survey statistics of the requirements of oral English learning resources

Resource name	Class 1	Class 2	Class 3
Oral English vocabulary resources R1	36	35	38
Oral English sentence pattern resources R2	25	26	37
Tuning practice resources R3	33	24	32
Oral English grammar resources R4	19	18	15
Creative expression resources R5	17	16	21
Scene dialog resources R6	35	38	37

Referring to the above statistical results on students’ needs, the performance of the three systems was compared on the basis of the recommendation accuracy for students’ personalized learning demands, and the comparison outcomes are presented in Figures 3–5. "System 1" and "System 2" refer to the online open course system that uses the B/S framework and the intelligent teaching system that uses deep learning techniques, respectively. The overall recommendation accuracy rate for the three classes' requirements is 92.47%, 94.02%, and 93.86%, respectively, and the suggested system in this study outperforms the other two comparison systems for the six spoken English learning resources for the three classes. By contrast, the average recommendation accuracies of System 1 for the three classes are 80.07%, 80.52%, and 80.31%, those of System 2 are 77.52%, 80.31%, and 78.81%, 80.62%, and 76.55% for System 2. The system in this paper has the highest accuracy rate for meeting the personalized needs of the students for English online learning, and it has a clear advantage over the other two compared systems. Almost all students indicated that they could accurately find the learning resources they were interested in and study them through this paper's system.

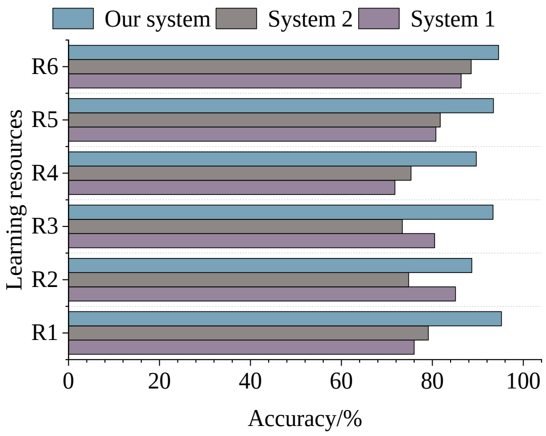

Figure 3: Comparison results of system recommendation accuracy(Class 1)

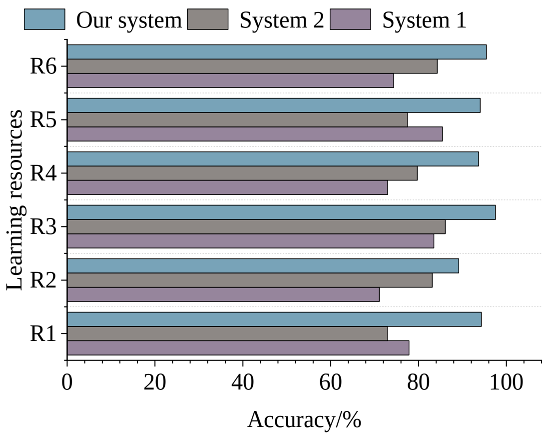

Figure 4: Comparison results of system recommendation accuracy(Class 2)

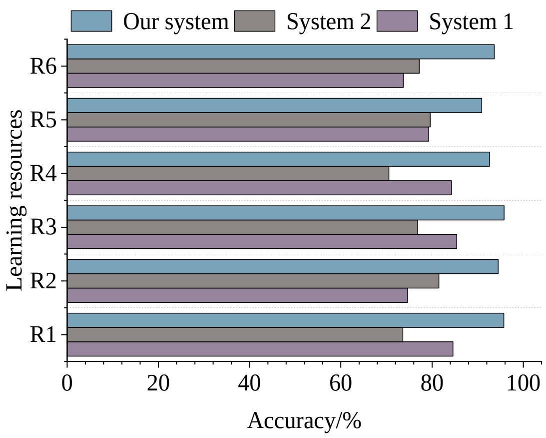

Figure 5: Comparison results of system recommendation accuracy(Class 3)

To further analyze the application of the recommended system, an experiment was carried out on the recommendation time related to students' needs. And the experiment results of the learning system are shown in Figure 6. It is clearly found that the recommended system in this paper performs better in terms of recommendation time. The average recommendation time obtained through experiments is 2.34 seconds, which is significantly smaller than 11.42 seconds and 8.51 seconds of System 1 and System 2, by increasing up to 79.51% and 72.50%. For the recommendation of the two comparison systems, as the data volume becomes larger, the recommendation time becomes larger and has poor stability with great fluctuations. Despite the fact that the recommendation time of the system designed in this paper will also become larger with the increase in data volume, the fluctuation is still very small, indicating that the personalized demand recommendation system recommended in this paper can react faster.

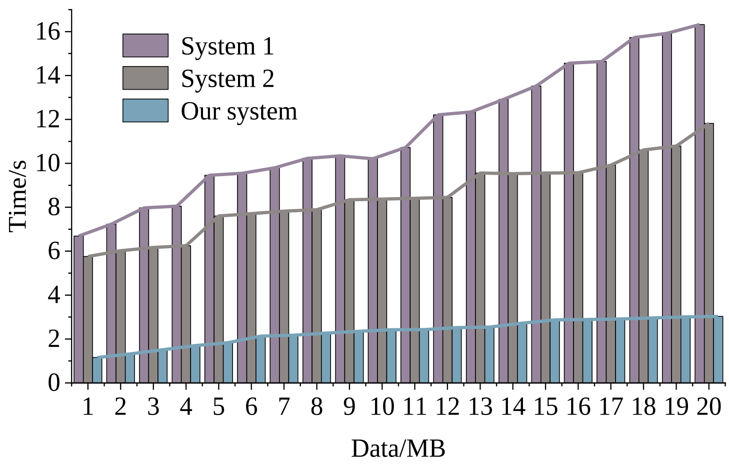

Figure 6: The recommendation time of the learning system

4.2.2 Effectiveness of oral training

The averages of speaking pre-test, speaking post-test, and the score gains of speaking between the experimental group and the control group were analyzed. The results from four classes are shown in Figure 7. The results show that all of the four classes' oral post-test scores are superior to their pre-test scores. The average oral scores of Class 1, Class 2, and Class 3 in the experimental group increased by 10.80, 7.09, and 8.66 points, which means that the increase is 15.09%, 9.82%, and 12.1%, respectively; while in the control group, the increase is 3.58 points and equals 5.04%. Furthermore, the increase in the experimental group has surpassed the one in the control group, which means that the use of digital technology in teaching English speaking is more effective than the traditional instruction. In addition, within the experimental group, the increase of Class 1 has far surpassed that of Class 2 and Class 3, meaning that the personalized and needs-oriented English speaking learning system is superior to the other two learning systems.

Speaking time is an easy measurement index for evaluating students' oral expression ability and can well reflect the change. Figure 8 indicates the lengths of the oral speaking test session for the experimental group and the control group. As compared to the pre-test, the speaking time after being taught has become longer in all the four classes. Speaking time of Class 1, Class 2, and Class 3 increased by 2.12 min, 1.78 min, and 1.83 min, while that of Class 4 has risen by 0.64 min. In the experimental group, the mean oral speaking length of Class 1 has raised by 176.05%, compared to 150.21% and 153% of Class 2 and Class 3, respectively.

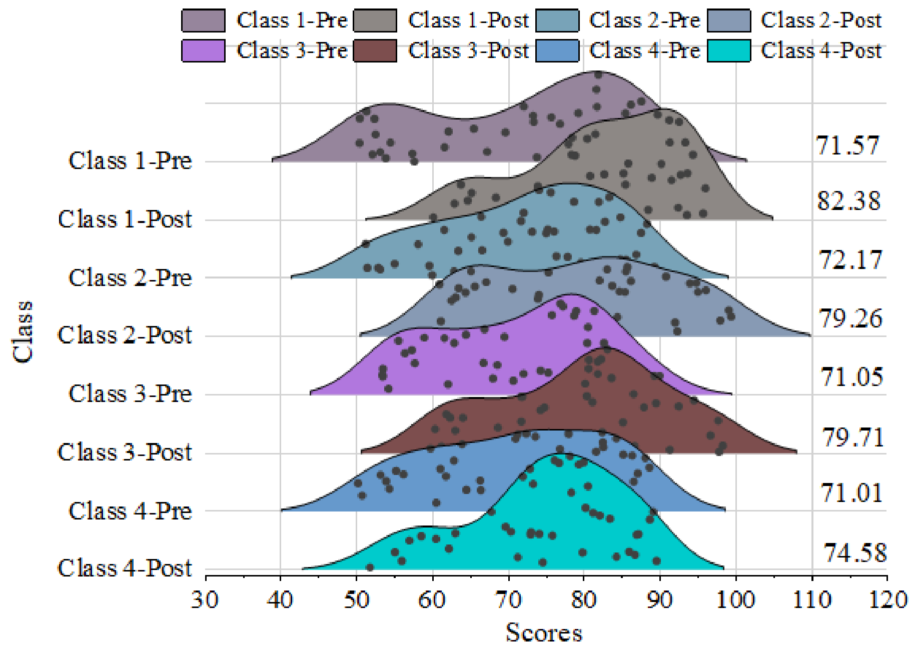

Figure 7: Pre-test and post-test results of oral English

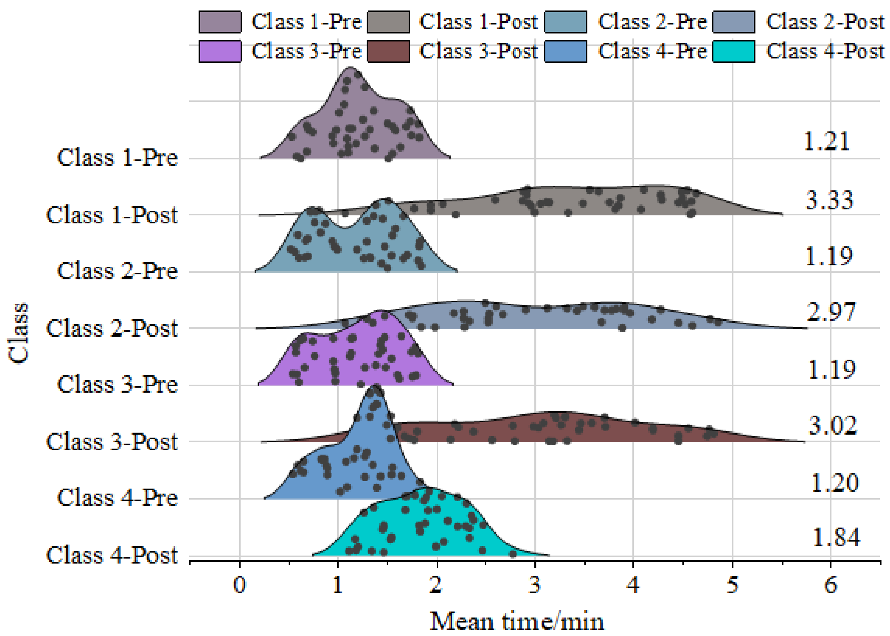

Figure 8: Pre-test and post-test results of average expression duration of oral English

5 Conclusion

In order to improve students' English speaking ability, research on the innovation of English speaking training mode based on the digital education environment is carried out, and strategies such as creating authentic contexts, expanding the speaking learning space, implementing differentiated teaching, and carrying out diversified evaluation are proposed. We design a resource recommendation method based on students' interests and preferences as well as an oral English learning system, and select students majoring in Business English from a certain school to carry out practical research. The system in this paper recommends learning resources with an accuracy rate of more than 90%, which is higher than the other two comparative learning systems, and the average recommendation time is 2.34s, which is 79.51% and 72.50% lower than that of the comparative system, and has a better resource recommendation effect. The experimental group's oral performance and oral expression time in the posttest were higher than the control group, and the oral performance was improved by 9.82% to 15.09%, and the oral expression time was improved by 150.21% to 176.05%, which proved that the digitalization-based English oral training model has a better promotion effect on students' spoken English. In the experimental group, the class adopting the system of this paper has the best oral performance and the length of oral expression, which further proves the superiority of the system of this paper for English oral training. The teaching mode of digital technology-enabled English speaking training is a good choice for cultivating students' language ability. In the future, teachers need to further promote the in-depth integration of digital technology and teaching, so that digital technology can truly become a booster for the high-quality development of spoken English teaching.

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