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# Research on AI-based "human-computer symbiosis" teaching mode

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**SUMMARY:** *In the epoch of intellectualization, intelligent technologies have been widely utilized in the education field. This not only brings opportunities for the progress of education and teaching but also puts forward totally new demands for talent cultivation under the background of the intelligent age. In this paper, we quantitatively represent learning resources from different directions in the context of human-machine symbiosis, and then use the hybrid collaborative recommendation algorithm in artificial intelligence technology to construct a personalized learning resource recommendation model based on human-machine symbiosis, and carry out experimental investigations on the model. After the model has obtained validation, a specially-made teaching model which centers on human-computer symbiosis is developed, this model acts as the technological foundation. After that, the practical teaching meaning of this teaching pattern is researched from four aspects: knowledge, skills, comprehensive using abilities, and cognitive abilities. Our research finds that the algorithm which this paper puts forward has a performance that is higher than the performance of the other three algorithms, with precision rate, recall rate and F1 value of 0.808, 0.728, 0.7659, respectively, which demonstrates the superiority of the hybrid recommender algorithm in the recommendation of teaching resources. In addition, the teaching mode of this paper is significantly different from the traditional teaching mode in four dimensions,* $P=0.005<0.05$, $P=0.026<0.05$, $P=0.007<0.05$, $P=0.005<0.05$, *proving the actual teaching effect of personalized teaching mode based on human-machine symbiosis. The research in this paper helps to improve the level of various abilities of college students, and also provides reference for the innovation of college teaching mode in the context of human-computer symbiosis.*

***KEYWORDS:*** *hybrid collaborative recommendation; learning resources; human-computer symbiosis; personalized teaching mode*

## 1 Introduction

In current time, a newly risen tide of information technology which is represented by artificial intelligence (AI) is greatly changing the overall situation of education [1]. In year 2023, the whole world AI education market has reached a worth of 62 billion dollar. In the educational field that covers many subjects, the proportion of adopting AI technology already exceeds 70 percent. The Education Ministry's Education Informatization 2.0 Action Plan puts emphasis on the necessity of pushing forward the full blending of AI into education and teaching, and the cultivation of brand-new teaching methods.In terms of professional construction, the relevant construction guidelines point out that majors should take the initiative to embrace intelligent technology and cultivate "AI+X" composite talents. These policies provide a clear direction and institutional guarantee for the design of educational intelligence [2-4].

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Along with various trades going through fast development, the demand for persons who have technique is continuously being pushed forward. This tendency has the function of promoting the transformation of educational systems and modes of cultivating talented persons.The research shows that 92% of enterprises are in urgent need of design talents with AI application capabilities, but there is an obvious disconnect between the talents cultivated by the existing education system and the market demand.To speak more concretely, the below problems are very clearly visible. The traditional teaching method has difficulty in following the fast speed of knowledge updating in the time of artificial intelligence. The nowadays curriculum frame has not caught up with the progress of technology. The evaluation method has an over-simplistic character. These questions are extremely obvious. This kind of non-balance in education supply and education demand therefore makes a deep reform in education domain to be necessary[5-8].

The deep combination of artificial intelligence technology and education has brought out the “Human - Machine Symbiosis” (HMS) model, which has become an important answer to this contradiction. The “human-machine co-existence” teaching model again defines the clear roles, responsibilities, and mutual interaction procedures of AI, teachers, and study participants [9]. As a teaching aid, AI is responsible for delivering some basic cognitive tasks, such as knowledge retrieval, scenario generation, and preliminary assessment, etc.; secondly, it intelligently matches the optimal learning paths to the students by capturing and analyzing their learning data in real time and combining their cognitive characteristics [10-13]. In the teaching and learning process, teachers focus on guiding students to develop critical thinking and value judgments about knowledge [14, 15]. This division of labor not only liberates teachers' productivity, but also enables learners to receive more precise cognitive support.

Researchers have given different interpretations about the theory of human-computer symbiosis and human-computer symbiotic relationships in education. Walsh et al [16] pointed out that the human-computer learning symbiosis system is placed in online education to create a flexible learning environment for students, and dynamically adjust the current status of student learning by considering their knowledge level and motivation.Wu and [17]his work group have carried out an all-round investigation concerning how the HMS model is able to promote educational outcomes. They have indicated that this model permits a change of the teacher's role from the one that is a controlling person to a helper who helps study. Furthermore, it makes the teaching and studying mode to have transformation through a number of methods. This thing pushes forward study experiences with individual differences, thus builds an impartial education environment, and brings in new methods on teaching and study; all of these hence are beneficial for the growth of students.He [18] reveals the role of digital intelligent machines in reconfiguring teacher-student relationships, reforming teaching content and methods, and teaching modes, thus driving teacher-student interactions towards a symbiotic model of “teacher-student-machine” triadic interactions.

While AI technology-driven human-computer collaborative teaching models have achieved significant results and promoted the development of HMS teaching models. Mi et al [19] investigated the enhancement of students' learning outcomes under multiple generative AI-based human-computer collaborative teaching models, and instructive, guided, and collaborative all contributed to the enhancement of students' performance and engagement, but the collaborative teaching model had the most significant effect. King et al [20] developed an AI-based automated virtual reality hands-on training system with non-directive mathematical questioning strategies to assist the interaction between the instructor and the students, which effectively improved the students' skills training. Li et al. [21] constructed a “teacher-student-machine” ternary structure teaching model through generative AI, and introduced the language learning sequence of “review-check-practice-progress”, which stimulated students' interest in learning and improved their core language competence. Abbass et al [22] drive AI technology to establish a logic-based symbiotic relationship with humans through AI-based machine education, which enables humans and AI autonomous systems to achieve two-way communication at the psychological level and obtain a reliable and stable symbiotic evolution. Xue and Li [23] pointed out that the HMS model promotes innovation in foreign language education and teaching by ChatGPT in terms of intelligent generation of teaching resources, human-computer dialogue training, language acquisition analysis and feedback, learning diagnosis, personalized learning path design, and post-course evaluation. Xuemei [24] evaluated the discourse dynamics of an AI-driven human-machine collaboration model in English language teaching in the context of symbiosis theory, which has personalized teaching as the main driver, and also has positive effects in terms of administrative efficiency, scalability, and adaptability, facilitating the symbiotic relationship between teachers and machines to become more inclusive. Li and Liao [25] described that AIs move from substitution to symbiosis in history education by presenting diverse historical perspectives, fostering students' critical thinking, and facilitating multidirectional teacher-student-AI interactions and collaboration.

In this paper, learning resources in the teaching process are classified and processed in multiple dimensions, and the relationship between them and the learning effect is established through similarity matching, which further determines the students' preferences and habits, and lays the foundation for recommending the media forms of resources suitable for students.Based on the idea of person-computer coexistence in teaching activities, we put forward that we should construct a custom-made study resource suggestion model which is based on person-computer coexistence. This result is obtained through the utilization of a mixed cooperative recommendation algorithm. After that, by means of data collections and measurement standards, model verification and discussion are carried out.In order to make the model better applied to classroom teaching, a personalized teaching model based on human-computer symbiosis is designed based on the model as a technical basis, and finally, the teaching effect of this teaching model is explored and analyzed in depth by using questionnaires and independent sample t-tests.

# 2 Recommendation of personalized learning resources based on “human-computer symbiosis”

In the domain of teaching and teaching activities, the idea of human-machine co-existence refers to the appearance of intelligent technology applications. This expresses a mutually beneficial coexistence and interaction pattern between those people who use technology and the electronic devices and equipment which are supported by intelligent technology. Starting from the viewing angle of the man-machine combination idea, the offering of personalized study materials is used to cultivate intelligent persons. It pushes personalized teaching that is driven by artificial intelligence technology and data, and also intelligent study inside the frame of human-machine coexistence. Below gives the introduction of the design flow for the suggestion of personalized study materials on the basis of "human-machine coexistence":

## 2.1 Representation of learning resources

### 2.1.1 Classification of learning resources

The study materials may be divided into two different kinds: the made-by-hand materials and the used materials. These include all the materials that can be obtained by learners in the process of learning. One resource is the expression form of knowledge concepts in a specific discipline. In the current time period, study resources display knowledge content through the form of written words and digital information. Their main expression ways contain videos, audios, pictures, multimedia tools, internet pages, teaching materials, actual-life examples, and test papers, and there are also other kinds.These types of resources may include one or more knowledge components. According to the actual demands of education, the types of resources are divided on the basis of the subject that they belong to, the knowledge components that they connect to, and the form that they are shown in. Through the classification of each kind of resource, every resource is able to have three characteristics.

### 2.1.2 Difficulty of learning resources

After considering the elements which influence the complexity of learning resources, a quantitative method for measuring the difficulty of learning resources is proposed for these resources.

(1) Knowledge point density $S_{DEN}$. When the knowledge points which are inside one course are regarded as a knowledge structure diagram, one main knowledge point together with its points which are under it compose a sub-knowledge structure diagram. Inside one certain sub-knowledge structure diagram, the number of sub-knowledge points that it contains is c $c(child)$ ounted, furthermore, the number of knowledge spots contained in the teaching material $c(dis(k))$ is counted. Therefore, the density of knowledge points is measured through the number of knowledge points that exist in the sub-knowledge structure diagram. The larger $S_{DEN}$ is,the larger the quantity of knowledge items that a learning resource includes, the more difficult it thus becomes to grasp. The reasons are just as what follows:

$$S_{DEN} = \frac{c(dis(k))}{c(child)} \tag{1}$$

(2) Knowledge point depth $S_{DEP}$. In the knowledge frame drawing, many different study moving paths can be built from the core knowledge idea to the edge knowledge ideas. This that can be said, it displays the amount of pre-requisite knowledge ideas which one must have held already, before one is able to study a special knowledge idea. The amount of these pre-required knowledge concepts exerts an influence on the difficulty degree of the test question. According to what this equation shows, and in line with the ontological order that exists between knowledge points, $c(dif(k))$ is the number of hierarchies where a knowledge point is located, beginning from the leaf-layer knowledge point. This can also be comprehended as the number of pre-required knowledge points that must be grasped in advance so as to obtain this specific knowledge point. $c(dif)$ is the number of layer numbers that span from the basal knowledge node to the final knowledge node inside the sub-knowledge structure graph. To speak specifically:

$$S_{DEP} = \frac{c(dif(k))}{c(dif)} \tag{2}$$

(3) Evaluation index $S_E$. After the research work of every resource has been completed, the learner $i$ evaluates the resource $X_i$ according to his/her learning. After that, the evaluation index is being fixed as the average number that comes from each learner's evaluation

on the learning resource. This point is holdable because:

$$S_E = \frac{\sum_{i=1}^{n} Xi}{n} \tag{3}$$

(4) Correctness $S_R$. This kind of assessment only acts as one of the methods for measuring the complication degree of a test question, as is shown in Equation 5 - 4, in which $c(total)$ is the accumulated number of cases where this problem has been discussed, $c(right)$ it represents the number of correct replies for all the questions which have already been finished, and $S_R$ is the ratio of correct answers to the related examination question. Therefore, the difficulty coefficient is constantly updated on the basis of the past students' question answer records. For:

$$S_R = \frac{c(right)}{\mathrm{c}(total)} \tag{4}$$

Therefore, the four measuring indexes of resource complexity are used as characteristic words and characteristic numerical values to calculate a vector of learning resource complexity measuring indexes $p$:

$$p = \left(S_{DEN}, S_{DEP}, S_E, S_R\right) \tag{5}$$

Measurement which is carried through on the foundation of a group of indexes measures the complication degree of study resources.

### 2.1.3 Similarity matching between learning resources

Even so, when we give suggestion about learning materials, we are not able to put forward all learning materials which include knowledge that students have not yet obtained. This method still cannot solve the problems of “information overloading” and “information direction losing.” Carry out the calculation on the cosine distance that is between the resources. A smaller numerical value thus implies a smaller difference in every dimension, hence it signifies that the two vectors represent more similar learning materials. We may suppose that there exist two learning materials which are named i and j. The similarity between these two kinds of materials is just like what below:

$$k^{i,j} = \cos(i, j) \tag{6}$$

Since each recommendation algorithm has its own advantages and disadvantages, we generally take a hybrid recommendation algorithm in the process of algorithmic combat. The mix here is not only the mix of algorithms, but also the mix of selected data, the mix of different scenarios, etc., so that the overall recommendation algorithm is optimal. Recommendation based on the sorting results obtained after weighted processing, the mixing formula for weighted mixing is shown in the following equation (7). For:

$$HybridR_w = \sum_{i=1}^{n} a_k * Rmd_k \tag{7}$$

where $a_k$ is the weight occupied by the Kth algorithm, and $Rmd_k$ is the Kth algorithm.

## 2.2 Overall Framework and Methodology for Personalized Learning Resources Recommendation

In the present research paper, according to the theoretical idea of human-computer mutual existence in educational teaching, a personalized learning resource suggestion method is proposed.Firstly, the relationship graph between knowledge points is constructed based on the ontology, and the students' test answers on the system platform are analyzed to carry out intelligent diagnosis of the students' learning level, get the knowledge points that the students have not mastered, and obtain the sequence of personalized knowledge points according to the topological sorting method. Then, according to the students' learning behavior to determine the relationship between it and the learning effect, to obtain the students' learning preference. Finally, according to the sequence of knowledge points to be learned and the difficulty of the learning resources, the resources that match the students are pushed.

### 2.2.1 Overall Framework for Personalized Learning Resource Recommendation

In this part, the detailed method for individual study resource recommendation is given. The whole structural framework of the resource recommendation is been drawn in Figure 1.

Step1: Input students' test question doing records and learning behavior.

Step2: Judge the students' knowledge structure and analyze the learning behavior to obtain the students' knowledge point level and learning habits or preferences.

Step3: Generate the sequence of knowledge points to be learned.

Step4: With reference to the learning behavior, recommend resources with corresponding difficulty.

Step5: Perform knowledge point checking and recommend parallel knowledge points.

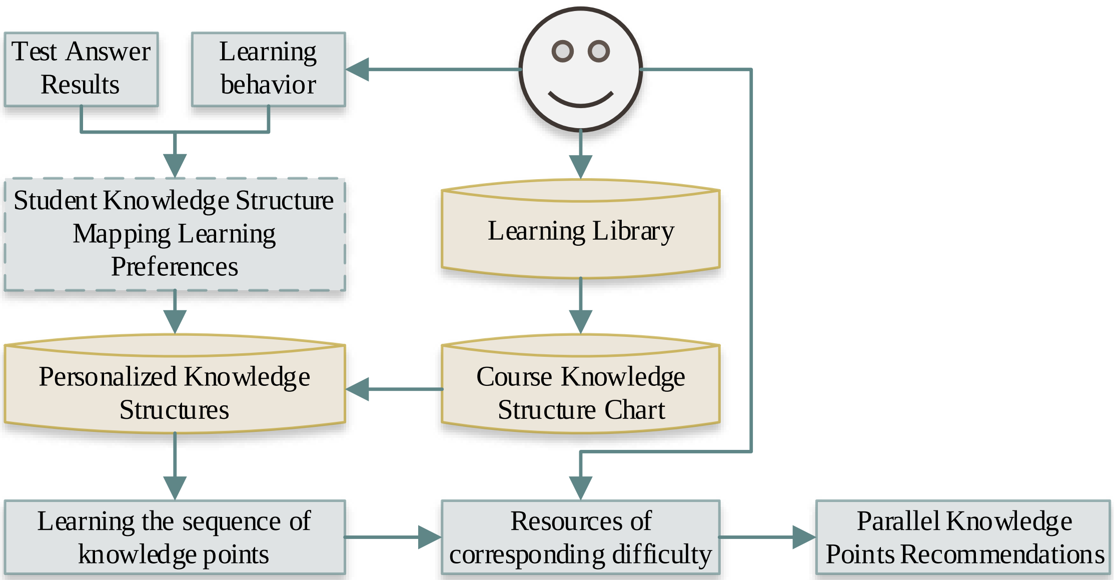


*Figure 1: The overall framework for resource recommendation*

### 2.2.2 Personalized Learning Resources Recommendation Methods

According to the requirements of learning objectives in learning, intelligent learning diagnosis of students' knowledge structure diagram is applied to judge the mastery of knowledge points. Analyze students' learning behavior to derive students' learning preferences, combined with a hybrid collaborative filtering algorithm for personalized learning resources recommendation [26].

Assuming that the ungrasped knowledge points are located in the sub knowledge structure graph structure $G'$, from the leaf nodes in the sub graph to the last knowledge point in the learning sequence is a learning path $L$. The difficulty of the resource is selected according to the proportion of the student-recommended knowledge sequence $L'$ in this learning path. This is shown in the following equation. Where $count(L)$ is the quantity of knowledge components from the root node to the last knowledge element in the sub-knowledge structure graph in which the sequence prepared for learning is located. $count(L')$ is the amount of knowledge concepts which are required to be studied. For:

$$p = \frac{count(L')}{count(L)} \tag{8}$$

The size of the $P$ value determines the difficulty of the recommended resources; the larger the value, the worse the mastery of the basic knowledge points of the student, and the need to recommend resources of lower difficulty. When the probability of mastery is greater than a certain value, the associated learning resources with higher difficulty are recommended.

(2) When the student's knowledge level is mastery of knowledge points

When the system confirms that the student has already hold the knowledge point, it therefore has the goal to prevent the appearing of blind areas that students may meet in the process of learning this knowledge point, then enter the “parallel” knowledge point learning. When the parallel knowledge point mastery is completed, the “subsequent” knowledge point learning.

An example of the sequence of knowledge points is shown in Figure 2, assuming that the sequence of knowledge points that students need to master is $L' = \{K2, K4, K6\}$, then $count(L')$ is 3 and $count(L)$ is 4 Containing $k1, k2, k4, k6$, after the system has carried out the verification that the student has already grasped the knowledge point, its objective is to avoid the occurrence of blind points which students may meet with when they study this special knowledge point. When all of them are mastered, the parallel knowledge point $k3$ needs to be learned.

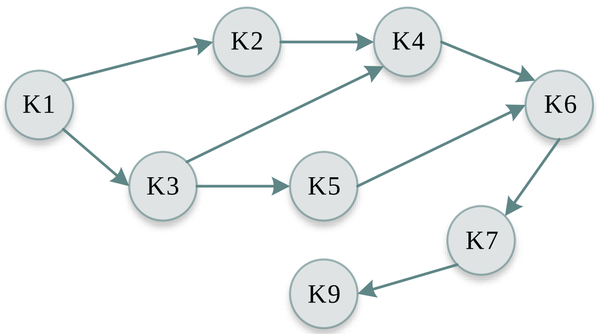


*Figure 2: Examples of knowledge point sequences*

## 2.3 Experimental validation analysis

### 2.3.1 Data sets

The data collection that is used for this recommendation algorithm is selected from the background data of an online education system. According to the demands of the topic, two groups of data are chosen: the course label data group and the user score data group. The course label data collection includes data items such as course ID, teacher ID, grade ID, subject ID, complexity degree, and time length.

### 2.3.2 Evaluation of indicators

The results that the assessment metrics' calculation gives can reflect the degree of good performance that a recommendation algorithm has. Furthermore, the method that is used for assessing the quality of recommendation results differs in accordance with what recommendation approach has been adopted.

(1) Scoring Prediction Indicator

The grading forecast index is employed to calculate the accuracy or completeness of the forecasted grade for the objective of evaluating the forecast results. Comprehensiveness indicates that the ratio of the count of recommended items to the total number of items that exist inside the system. A higher level of comprehensiveness means a broader scope of suggested items, which therefore brings about the long-tail effect. Other indices which people utilize for measuring accuracy are mainly the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE). MAE, that is an absolute measuring method, is calculated in the way which is shown in the following equation (9):

$$MAE = \frac{\sum_{u,i\in T} |r_{ui} - p_{ui}|}{|S|} \tag{9}$$

The expression formula of Root Mean Square Error (RMSE) is given in the below equation (10). To speak specifically:

$$RMSE = \sqrt{\frac{\sum_{u,j\in T} \left(r_{uj} - p_{uj}\right)^2}{|S|}} \tag{10}$$

In the above equation $r_{uj}$ is the historical rating of item j by user u, $p_{uj}$ is the predicted rating of item j by user u, and $S$ is the total number of ratings by users in the test set.

(2) Item set recommendation metrics

The metrics for itemset recommendation are precision and recall and weighted harmonic mean of precision and recall, etc., according to the correctness of the predictions on the test set [27]. There are four cases as follows:

TP: The number of bars that predict the positive class as positive.

FN: The number of entries that predicted the positive class as a negative class.

FP: The number of entries that predict the negative class as positive.

TN: The number of submitted results which predicted the negative kind as a negative kind.

The accuracy rate is the proportion of correctly forecast items in all the data that are predicted as positive categories. This value is calculated in the manner that is shown in the following equation (11). With regard to:

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

Recall refers to the proportion of the entries correctly predicted to be recognized among all the data that truly belong to the positive category. It is calculated in the way which is shown in the equation (12) below. To speak concretely:

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

When we make evaluation on the effectiveness of recommendations, a higher precision rate, which means a bigger count of positive categories inside the recommended outcome, hence it shows a more good result. At the same time, a higher recall rate, which represents that positive categories have a bigger proportion in the output of recommendation, hence also indicates that the recommendation system has a better performance.However, precision and recall are often contradictory to each other, and one value is very high while the other value is low. The appearance of F-Measure is to weigh the precision and recall, and to reconcile the gap between the two values. If the F-Measure value is very low, it means that at least one of the precision and recall values is very low, and the recommendation effect is poor; on the contrary, it means that the precision and recall are relatively stable, and the evaluation result is better.

The F-Measure is calculated as follows in equation (13), where $\alpha$ is utilized to measure the degree of the reconciliation's accuracy and comprehensiveness. For:

$$F - Measure = \frac{\left(\alpha^2 + 1\right) * Precision * Recall}{\alpha^2 * (Precision + Recall)} \tag{13}$$

We often set $\alpha$ in F-Measure to 1, i.e., the formula for the F1 value is shown in Eq. (14) below, and the range of F1 is (0-1). For:

$$F1 = \frac{2 * Precision * Recall}{(Precision + Recall)} \tag{14}$$

### 2.3.3 Experimental results

By the way of analysis and comparison of the experiment results, we carry out assessment on the prediction effect of the traditional model and the model which is put forward in this research paperIn this sub-section, two different groups of experiments have been conducted by us. Experiment One carries out the evaluation on the score prediction effect of many different similarity models through the use of different nearest-neighbor numerical values. At the same time, Experiment II has carried out evaluation on the recommendation precision rate, recall rate, and F1 index of various different recommendation algorithms. The goal of these experimentations is to carry out analysis on the recommendation performance of every single recommendation algorithm.

(1) Experiment 1

Two improvements of the traditional cosine similarity include reducing the effect of scores from highly active users and adding a punishment according to the time difference between users' scoring on two courses. Under this situation, we carry out a comparison on the Root Mean Squared Error (RMSE) values among four models. These models are the conventional cosine similarity (Sim), the cosine similarity which gives a penalty to active users (Sim - h), the cosine similarity which penalizes the time gap between ratings (Sim - f), and the cosine similarity which combines two penalties (Sim - mix), this experiment's purpose is to evaluate the effect of recommendation algorithms that use many different similarity models for nearest-recall. This paper also studies the influence that the number of nearest neighbors, which is named as K, produces on the error value of the system. To speak specifically, four groupings of K numerical values (5, 10, 15, and 20) have been chosen by us. We carry out the calculation of Root Mean Square Error (RMSE) values for the purpose of performance evaluation. The RMSE numerical values for diverse similarity models are given inside Table 1.In many kinds of nearest-neighbor situation, the root mean square error values of the three strengthened similarity models are smaller than that of the old-style cosine similarity model. The error optimization degree of Sim-h and Sim-f is very similar, therefore Sim-mix can get the most good result. When we set K value as 5 or 10, because the time spaces between the goods scored by users are not long, therefore the penalty gives a comparatively small effect on the similarity. Under this circumstance, the behavior of Sim-f has a tiny superiority over the performance of Sim-h.On the opposite side, when the K value is equal to 15 and 20, because we select a bigger quantity of nearest neighbors, the time interval between user-marked items becomes overly long. This therefore brings about an enhancement of the time punishment. Therefore, the achievement of Sim-h is better than that of Sim-f. The Sim-mix is got through the combination of Sim-h and Sim-f. Hence, this framework takes into consideration both the penalty that is for active users and also the time-related penalty. It possesses the minimum error and thus obtains the optimal effect.When we carry out the setting that the value of the nearest neighbor K is 5, the four models can not obtain effective results. On the opposite side, when K value takes 15, the root mean square error arrives at its smallest value, hence the model performance is in its best condition. Therefore, in order to promote the degree of similarity, when the K numerical value is 15, the Sim-mix model is the most appropriate selection.

*Table 1: RMSE of different similarity models*

| Similarity model/Neighbor number K | 5 | 10 | 15 | 20 |
|---|---|---|---|---|
| Sim | 1.121 | 1.106 | 1.042 | 1.111 |
| Sim-h | 1.118 | 1.077 | 1.026 | 1.036 |
| Sim-f | 1.117 | 1.069 | 1.027 | 1.049 |
| Sim-mix | 1.105 | 1.039 | 0.977 | 0.988 |

(2) Experiment 2

This experiment carries out the assessment on the recommendation influence of various recommendation models. It achieves this through the comparison of the accurate rate and the recall rate of four models: User Collaborative Filtering (User - CF), Item Collaborative Filtering (Item - CF), Content - Based Recommendation (CB), and Hybrid Recommendation (HybridR).Table 2 gives the result situations of the accuracy rate, recall rate, and F1 value for each different recommendation algorithm. In these algorithms, the user collaborative filtering algorithm shows the smallest numerical values on precision ratio, recall ratio and F1 score, therefore it indicates that the recommendation performance is not up to standard. Behind this place, there are the item collaborative filtering and the recommendation algorithms which are based on content.The hybrid recommendation algorithms display a more excellent recommendation result when compared with the other three algorithms, having numerical values of 0.808, 0.728, and 0.7659. This reason lies in the weighted combination which is made of Item - Collaborative Filtering (CF) and Content - Based (CB) methods. The present research discusses and handles problems including the cold-start question and the long-tail occurrence by means of a method which has been optimized. Furthermore, it promotes the enhancement of the precision rate, the recall rate, and the F1 value. This proves that the algorithms which are put forward in this paper are more suitable for the recommendation of personalized teaching resources.

*Table 2: Comparison of the accuracy, recall rate and F1 value of the algorithm*

| Index | User-CF | Item-CF | CB | HybridR |
|---|---|---|---|---|
| Precision | 0.556 | 0.641 | 0.626 | 0.808 |
| Recall | 0.496 | 0.574 | 0.567 | 0.728 |
| F1 | 0.5243 | 0.6057 | 0.5950 | 0.7659 |

# 3 Teaching models that incorporate human-computer symbiosis

## 3.1 Instructional model design incorporating human-computer symbiosis

### 3.1.1 Creating an intelligent classroom

When students encounter problems that are difficult to understand or want to have a more in-depth and detailed understanding of a certain topic, they can learn or communicate and discuss with their teachers and classmates through the human-computer symbiosis-based personalized learning resources recommended supplementary materials [28]. In addition, teachers through the human-computer symbiosis-based personalized learning resources recommended method of feedback on student learning can determine the student's nearest development zone, for carrying out accurate teaching in the following stage of classroom teaching activity, it is needed to provide a data basis which satisfies the special demands of students.

### 3.1.2 Enhancing intelligent learning styles

The recommendation method for individualized studying materials which is constructed on the basis of human-computer mutual existence provides strong technical support for students' intelligent and personal studying. The method of the intelligent type learning is displayed in the Figure 3.Different strategy support will be pushed to learners according to each learner's different learning styles, learning preferences, learners' different interests and specialties, etc. This allows students to make clear the important and difficult points of their own learning in classroom teaching, and they will be more actively engaged in classroom learning, which in turn improves students' linguistic knowledge, linguistic skills, comprehensive application of language, and higher-order cognitive abilities.

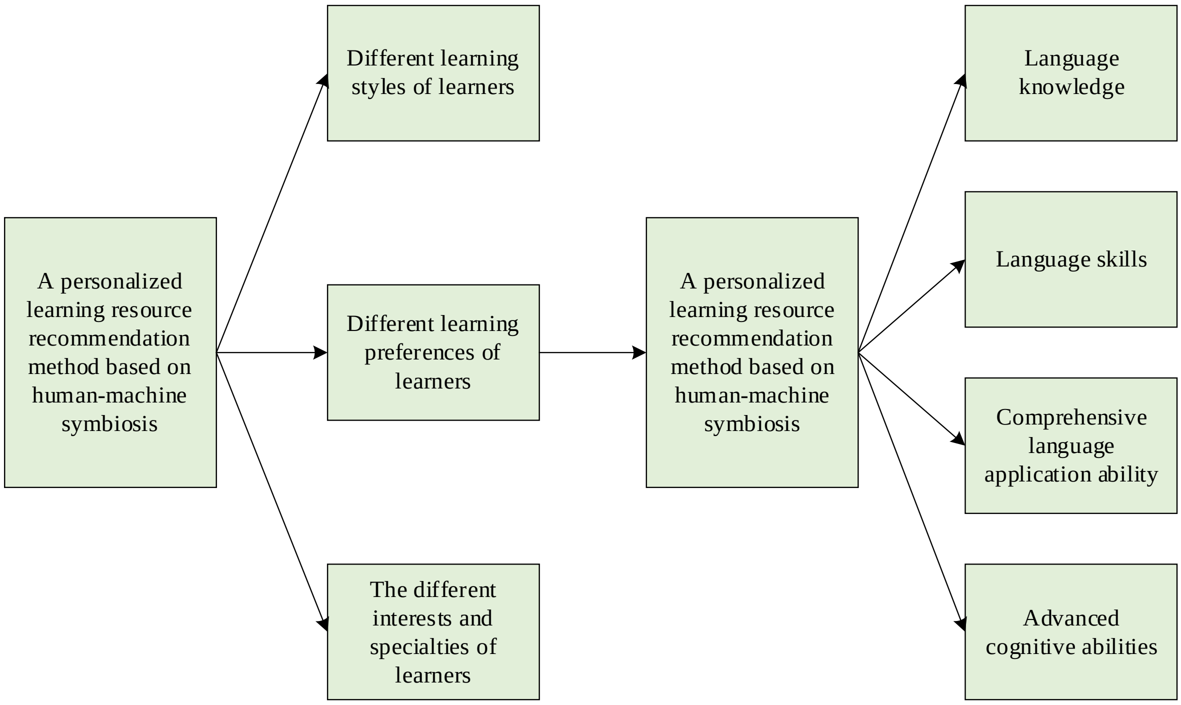


*Figure 3: Intelligent learning methods*

### 3.1.3 Intelligent Teaching and Learning

The personalized learning resources recommendation method based on human-computer symbiosis will dynamically monitor the learning behavior and learning situation of learners, can accurately determine the gap between the learning level of learners at this stage and the target requirements, and flexibly adjust the appropriate learning methods according to the learning situation and learning goals of learners, which puts a noteworthy impact upon the teaching method, the way of teacher-student interaction and communication, and the way of student learning. The personalized learning resources recommendation method based on human-computer symbiosis brings rich teaching resources and advanced teaching means for college teaching, which in turn allows the college teaching classroom to enter a new development of wisdom space.

## 3.2 Experimental design of teaching model

This section has the objective to verify the effectualness of the integrated human-computer mutual symbiosis teaching model. It also makes efforts to explore whether this model can promote students' English learning abilities in English classroom teaching. Therefore, this section thus puts emphasis on the procedure that is for experimentally verifying the teaching model which is founded on the integrated human-computer symbiosis. After that, the results which these experiments have gotten are done analysis and are given out. In order to obtain objective and scientific experimental data, the evaluation scale of students' English learning ability is compiled before conducting the teaching experiment, and the design of the teaching experiment is carried out to introduce the experimental process and experimental methods, etc., and the results of the experiment are analyzed through the data analysis software of SPSS data statistics to draw experimental conclusions. Details are as follows:

### 3.2.1 Purpose of the experiment

Through the carrying out of teaching experiments, the goal is to confirm the effect of the human-computer symbiosis teaching model on the enhancement of students' English ability. In addition, this paper tries to make clear the effect that related factors have on the English learning ability of students.

### 3.2.2 Experimental Objects

In order to ensure the experiment's true degree and repeatable property, this research randomly selected X College which is located in Y City to be our investigation object.At the same time, for the purpose of simplifying the comparison in the process of analyzing the experimental results, the objects of the experimental research have undergone random arrangement. The person in charge of the school's English teaching research group arbitrarily selected two classes of students from among the four classes in the school to carry out teaching experiments and retain follow-up records, and the number of control class and experimental class were both 50, and the experimental class adopted the human-computer symbiosis The experimental class was taught in the human-computer symbiosis mode, while the control class was taught in the traditional classroom lecture mode.

### 3.2.3 Experimental Methods and Procedures

According to the needs of the research problem as well as the actual situation, and considering the advantages and disadvantages of different research methods, this experiment synthesizes and adopts quantitative methods to conduct the research so as to be able to interpret the experimental results more comprehensively and accurately in order to draw more convincing conclusions. In the period from March to July in year 2023, one experiment was conducted by us. We have employed two different teaching methods to carry out teaching for the experimental class and the control class. For more specifically speaking, the experiment class adopted a teaching mode which takes human-computer symbiosis as the center, meanwhile the contrast class used the traditional teaching way.For ensuring the accuracy of the teaching experiment, the same English teacher gives lessons to both of the two classes, and the quantity of class hours for each class is set to be exactly equal.

(1) Questionnaire Design

This experiment’s questionnaire was made according to the four-dimension evaluation index frame of students’ English learning ability level. This frame includes four big parts: the knowledge of language, the skills of language, the whole ability of language usage, and the advanced abilities of cognition. In order to let questionnaire items become more lifelike, pre-test questions were utilized by us to carry out design and modification work for questionnaire topics.After the teaching experiment, the results of the teaching experiment were statistically and analytically analyzed through SPSS data analysis software.

(2) Reliability test

We have used Cronbach's coefficient to assess the questionnaire's reliability, and the results of this reliability assessment are shown in Table 3. One widespread rule says that if the numerical value of Cronbach's coefficient goes beyond 0.7, the questionnaire may be regarded as having relatively higher trustworthiness.With regard to this questionnaire, the Cronbach's alpha coefficients of language knowledge, language proficiency, total language using ability, and advanced cognitive ability all are higher than 0.7. This gives indication that the four aspects of the test projects inside this questionnaire have a high degree of internal consistency, and the reliability of the results of the questionnaire test is in line with the requirements of the analysis. In addition, the Cronbach reliability coefficient value of the whole scale, which is calculated by all questionnaire data, is equal to 0.812. After the completion of standardization processing, the Cronbach coefficient is 0.813, which obviously exceeds the threshold value 0.7. This indicates that the questionnaire has high reliability and authenticity, which accords with the actual situations of the persons answering the questions and meets the standards for the analysis of the questionnaire data.

*Table 3: Reliability test results*

| Dimension | Cronbach's coefficient | Standardized Cronbach's coefficient | Number of items |
|---|---|---|---|
| Language knowledge | 0.826 | 0.827 | 10 |
| Language skills | 0.868 | 0.869 | 10 |
| Comprehensive language application ability | 0.738 | 0.739 | 10 |
| Advanced cognitive abilities | 0.816 | 0.817 | 10 |
| All questionnaire data | 0.812 | 0.813 | 40 |

The validity degree of the experiment’s questionnaire was ascertained through an evaluation which utilized the KMO test and Bartlett's sphericity test. These experiments were utilized to assess the effect of the questionnaire's measure items for language knowledge, language capability, overall language application abilities, and high-level cognitive skills, each one by one.The results of this validity examination are shown in Table 4.In the experiment for checking validity, the result of KOM test lies in the scope which is from 0 to 1. The more near the test result approaches 1, the more good the data conforms to the research criteria.With regard to the questionnaire evaluations of language knowledge, language capability, total language application capability, and high-level cognitive ability, the computed outcomes of the KMO test are 0.778, 0.874, 0.729, and 0.817 respectively.Every single one among these digital numerical magnitudes has a value that is larger than 0.7. The results of Bartlett's sphericity examination display that the examination numerical values for the four aspects — that is, language knowledge, language abilities, comprehensive language application abilities, and high-level cognitive abilities — are 208.404, 233.116, 131.074, and 220.451 separately.In addition, the relevant significance Sig numerical values are under 0.05. This result gives us the indication that obvious differences exist between these five dimensional aspects. Therefore, the data got from this questionnaire's outcomes can be regarded as having high validity, and the measuring items satisfy the standards needed for analysis and research.

*Table 4: Validity test results*

| Detection content | | Language knowledge | Language skills | Comprehensive language application ability | Advanced cognitive abilities |
|---|---|---|---|---|---|
| The measurement of the suitability of KMO sampling | | 0.778 | 0.874 | 0.729 | 0.817 |
| Bartlett's sphericity test | Approximate chi-square | 208.404 | 233.116 | 131.074 | 220.451 |
| | Degree of freedom | 40 | 40 | 40 | 40 |
| | Significance | 0.001 | 0.002 | 0.006 | 0.007 |

# 4 Experimental test results

## 4.1 Analysis of linguistic knowledge data

We altogether distributed 50 survey questionnaires for the experimental group's pre-test and post-test. Hence, all 50 questionnaires were got back successfully and were considered valid, hence this brings about a 100% valid return rate. Figure 4 carries out an inspection on the language knowledge of the experiment group in the pre-test and the post-test. According to the data that the figure shows, the average values of the experiment group's language knowledge in the pre-test and the post-test are 2.565 and 3.512 separately. The pre-test data that belongs to the experimental group is 0.947 smaller than the post-test data. After this step, an independent sample t-test has been conducted by us on the pre-test and post-test data of the experiment group. It was found by us that a notable difference exists in the language knowledge data of the students who are in the experimental group, with P = 0.003, hence this value is smaller than 0.05. Therefore, thus, the research shows that the personalized teaching mode which is built on human-machine coexistence can, with high efficiency, raise students' language knowledge level of mastery.

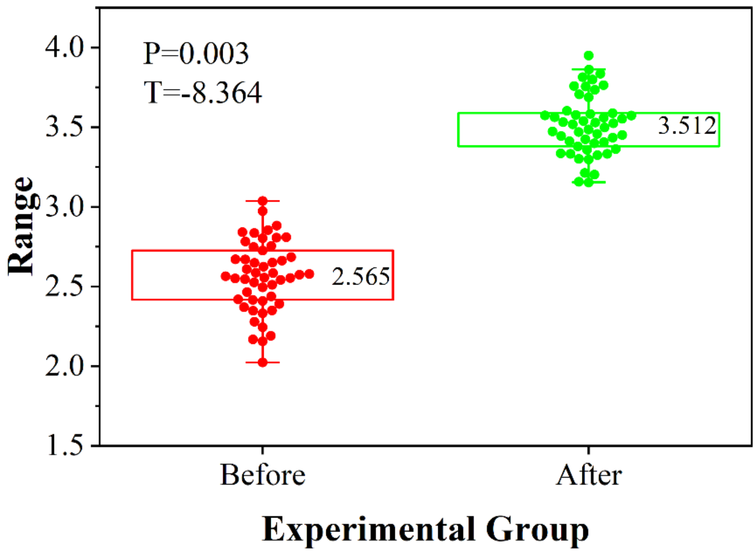


*Figure 4: The language knowledge of the experimental group was tested before and after*

Using the identical method that was talked about before, an evaluation of the pre-test and post-test of the language knowledge for the control group has been carried out. The result situations of the pre-test and post-test of the control group on the aspect of language knowledge are shown in Figure 5.After analysis, it can be seen that the mean values of language knowledge in the pre-test and post-test of the control group are 2.536 and 2.527, respectively, and it can be intuitively found through the test data that the students' language knowledge has not been improved after regular teaching. According to this, one more independent samples t-test has been carried out. Our experiment has obtained a P-value of 0.206 and a T-value of -7.116. This result gives the idea that there do not exist obvious differences between the pre-test and post-test data with regard to the language knowledge that is held by the students of the control group.

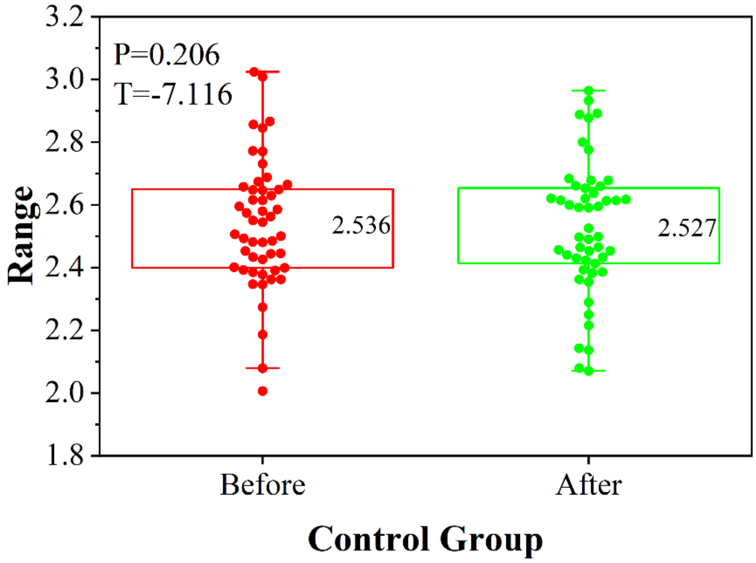


*Figure 5: The pre - and post-test results of language knowledge in the control group*

After that, therefore, we will put our attention on the analyzing of the post-test data which come from the experimental group and also the control group. The result of the analysis for the language knowledge post-test data are displayed in Figure 6. Through the checking of the data in the figure, we are able to see that the post-test average marks of the experiment group and the comparison group are 3.512 and 2.527 respectively. The average score of the experiment group has 0.985 points more than the score of the comparison group. On the basis of this result, therefore, we can give a primary judgement that individual teaching which is constructed on human-computer mutual existence has better effect on promoting the promotion of language knowledge level.An independent samples t-test was then conducted on the posttest data of the experimental and control groups, and it was found that P=0.005<0.05, T=2.064, i.e., there was a significant difference between the posttests of the experimental and control groups. It was further verified that the effect of personalized teaching based on human-computer symbiosis was superior to the conventional teaching method conducted by the control group.

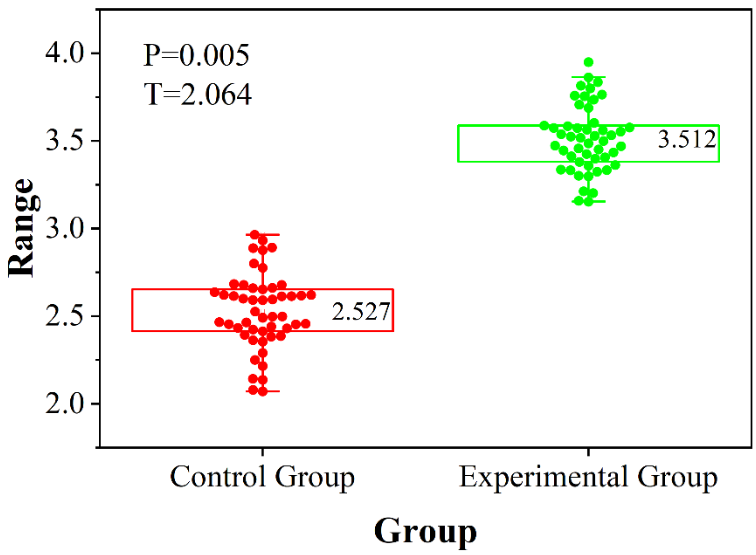


*Figure 6: The results of post-test data analysis of language knowledge*

## 4.2 Analysis of data on language skills

At first, the data which are about the students' language ability have been processed and inspected. After that, the average marks of the pre-test language ability data of the students in the two groups were calculated. At last, an independent sample t-test has been carried out to judge whether there is a notable difference between the two groups' data. The results got from the analysis of the gap between the pre-test of the experiment group and the control group are shown in Figure 7.After we carry out analysis and do calculation work, it can be clearly seen that the average score values of the verbal ability data for the experiment group and the comparison group are 2.481 and 2.531 respectively. Furthermore, the average scoring value of the experiment group is 0.03 lower when compared with the control group. In terms of the independent samples t-test, the value of p is 0.058, that is, p>0.05, and the value of p indicates that there is no significant difference between the verbal skills of the experimental and the control groups, which means that the initial level of verbal skills of the subjects in the two groups is relatively the same, and so the the study is statistically significant.

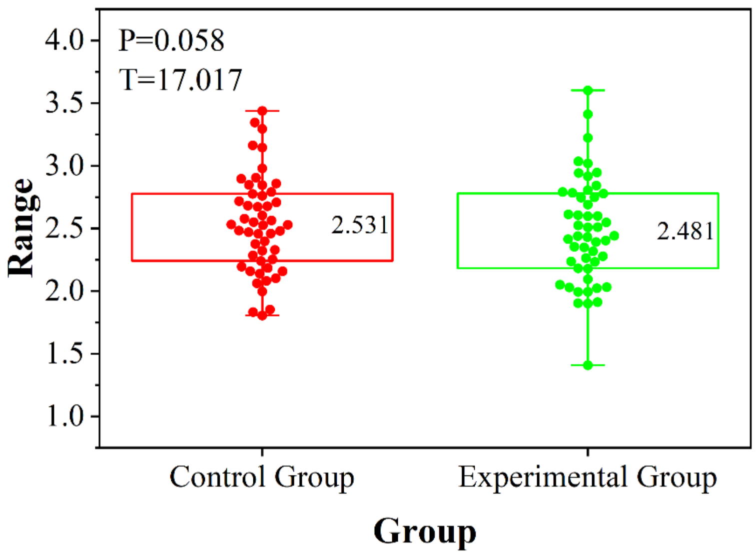


*Figure 7: The pretest differences between the experimental group and the control group*

For confirming whether an obvious difference exists between the post-test language skill data of two groups of students, the average scores of this data were calculated. After that, we have executed an independent sample t-test. The results that this analysis gets, which makes comparison between the post-test outcomes of the experiment group and the control group, are shown in Figure 8. After one semester's continuous research experiment, the participants of two groups all were required to finish a post-test, for the collecting of data that is about their language ability levels. The average score of post-test which belongs to experimental group is 3.278, as for the average score of control group, it is 2.647. According to these outcomes, it can be first deduced that personalized teaching built on human-computer mutual existence is more effective in promoting students' language abilities.After this step, we have carried out an independent samples t-test. The p-value that we have obtained is 0.026, which is smaller than 0.05. The p-value tells us that a quite clear difference exists on language ability between the experiment group and the comparison group.Therefore, it can imply that after one semester of teaching experiment, between these two groups, the gap in language ability is significant. According to these results, the research can get the conclusion that, when compared with traditional teaching ways, individualized teaching which is established on man-machine symbiosis has a good effect on the English study of students who are in the experimental group.

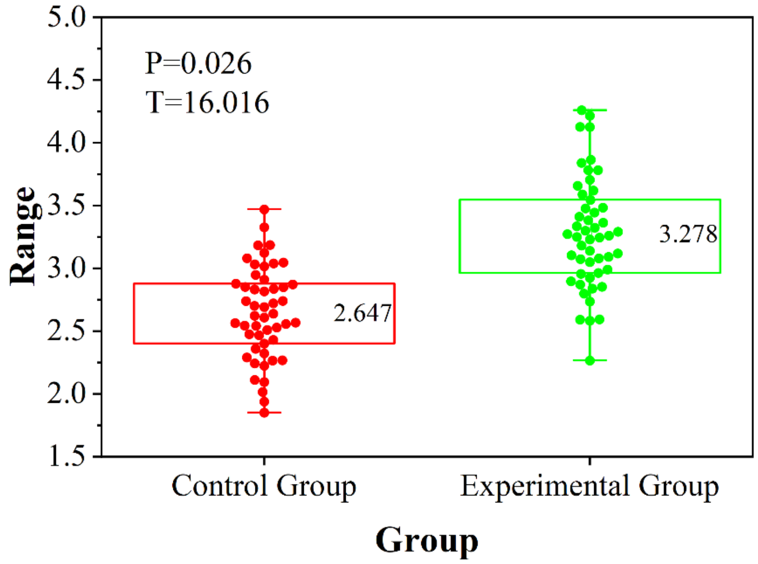


*Figure 8: The results of the post-test difference analysis*

## 4.3 Analysis of data on comprehensive language proficiency

The change of the whole language using ability can directly reflect the teaching result. For the purpose of eliminating the influence brought by the difference of students' whole language using ability on the results of the following research, therefore it is necessary to carry out a pre-test analysis on the data which is about the whole language using ability, Figure 9 gives out the results of the pre-test analysis which is for the experimental group and also the control group. The average scoring of the experimental group is 2.632, while that which belongs to the control group is 2.828. The Sig numerical value is situated at 0.716, which is higher than 0.05. This shows that the overall language use abilities of these two groups of students are similar, hence there is no obvious gap existing between them. Because of this reason, therefore, the experiment can be carried out.

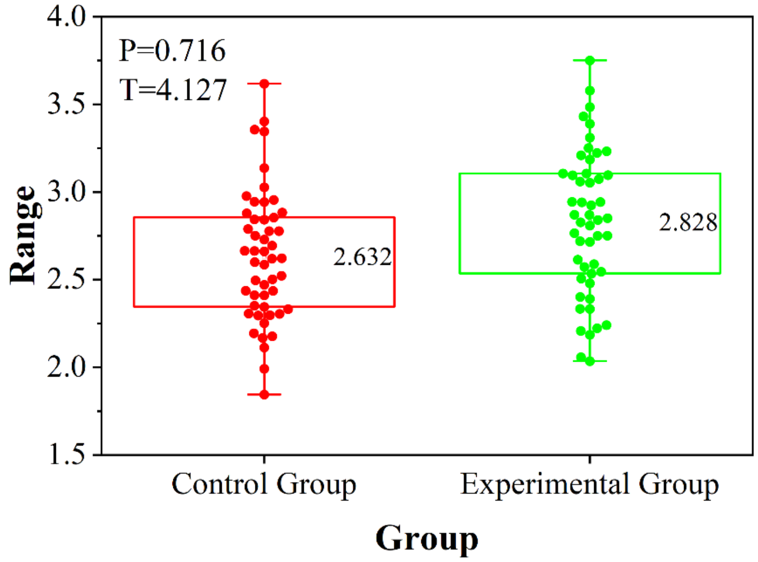


*Figure 9: The pretest analysis results of the experimental group and the control group*

After each semester's teaching work for the two groups of students was finished, the instructor conducted a post-measurement on their overall abilities of language use. This action was taken to measure the effect of the teaching model which this paper puts forward in the actual teaching situations. The result of the after-test analysis that belongs to the experiment group and the comparison group are shown in Figure 10.The average numerical value of the after-experiment overall language application ability of the students who are in the experimental group was 3.533, which has surpassed that of the control group, which is 2.878. Furthermore, every Sig value was lower than 0.05, which hence indicates an obvious difference in the overall language using capability between these two groups of students.This shows that the extra learning materials given by the teaching method put forward in this paper can satisfy the demands of students and accurately find and solve the shortcomings in their knowledge condition. Therefore, the total language ability of the students who are in the experimental group has seen a very notable enhancement.

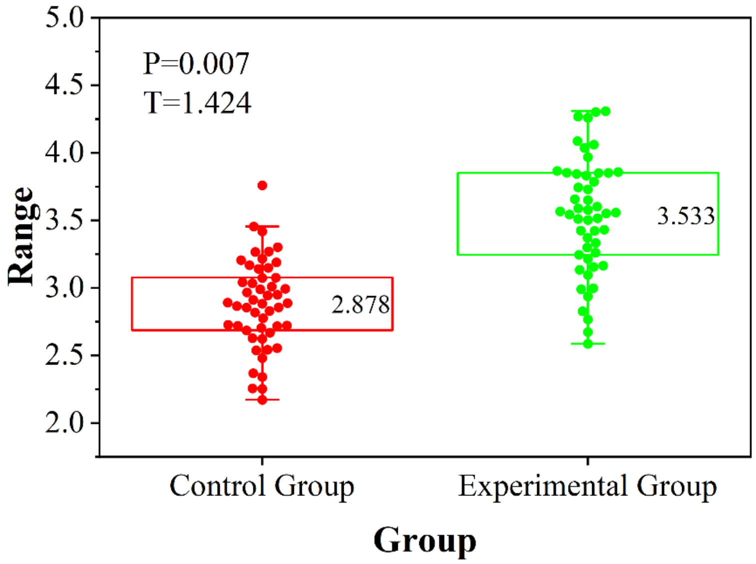


*Figure 10: Post-test analysis results of the experimental group and the control group*

## 4.4 Analysis of data on higher-order cognitive abilities

Inside this small section, pre-tests and post-tests were given out to students in both the experiment group and the control group in order to measure their high-level cognitive abilities. After this step, the results that these tests gave were analyzed by means of the SPSS software package. The data that is analysis concerning the higher-order cognitive ability are shown in Table 5. Before the intervention was carried out, the difference between the average scores of advanced cognitive ability in the experiment group and the control group was 0.073, and its P-value was 0.053. This result hence indicated that there did not exist statistics-based notable differences between the two groupings. After the intervention was carried out, the difference of the average points of high-level cognitive abilities between the experiment group and the control group got to 1.151. The chi-square examination for variance significance gave out a p-value of 0.006. Because this p-value was smaller than 0.05, it thus showed that between the two groups, the variance had a statistical significance difference. To sum up, when we make comparison with the traditional teaching method, the student-focused teaching pattern which is built upon man-machine interaction possesses a quite remarkable influence upon the improvement of students' high-level cognitive abilities. The teaching mode that is put forward in this paper provides clear strategy help for learners, when we consider their personal learning ways, personal preferences, personal interests, and personal domain ability. Therefore, this thing has the effect of promoting the promotion of students' higher-order cognitive abilities.

*Table 5: Data analysis of advanced cognitive abilities*

| Group | | N | Mean | P-Value | T-Value | Mean Difference | Sig(2-tailed) |
|---|---|---|---|---|---|---|---|
| Before | Experimental Group | 50 | 2.473 | 0.359 | 2.334 | 0.073 | 0.053 |
| | Control group | 50 | 2.546 | | 2.334 | 0.073 | 0.053 |
| After | Experimental Group | 50 | 2.517 | 0.006 | 0.324 | 1.151 | 0.005 |
| | Control group | 50 | 3.668 | | 0.324 | 1.151 | 0.005 |

# 5 Conclusion

Inside the epoch of intelligence, the intellectualized teaching pattern has already caused an obvious change that is great in the educational system. The traditional teaching pattern is having difficulty in following the developing path of smart education. Therefore, it is of great necessity to strengthen the investigation regarding the innovation of teaching patterns in the intelligent epoch. The present article is constructed upon the theoretical framework of human-computer mutual symbiosis. One personalized study resource suggestion model which is based on artificial symbiosis is constructed by utilizing one mixture suggestion calculation method. For making this model have better support ability to teaching activities, we have designed one teaching model which is integrated by human-computer symbiosis. Furthermore, an all-rounded exploration and analysis on the research methods have been conducted by us. The obtainments of this research are as what follows:

(1) When the value of K is 15, the root mean square error of the hybrid similarity method is the smallest, with a value of 0.977, while the root mean square of the other similarity methods is 1.042, 1.026, and 1.027, which indicates that the performance of the hybrid similarity method is optimal. In addition, the recommendation effect of this paper's algorithm is better than the other three algorithms, with precision rate, recall rate and F1 value values of 0.808, 0.728, 0.7659, which fully validates the effectiveness of this paper's model in personalized learning resources recommendation.

(2) Before the teaching experiment intervention was carried out, there existed no obvious differences between the teaching model put forward in this paper and the traditional teaching model, and the P-value is smaller than 0.05. After we conducted one semester of teaching experiment intervention, we have discovered that obvious differences exist between the teaching model put forward in this paper and the traditional model, in the aspects of language knowledge, language ability, comprehensive language application ability, and high-level cognitive ability.The corresponding P values were respectively 0.005 (lower than 0.05), 0.026 (lower than 0.05), 0.007 (lower than 0.05), and 0.005 (lower than 0.05). In conclusion, the teaching mode which is built upon human-computer symbiosis has obvious prominent performance in promoting many kinds of indexes of students. This also can demonstrate the actual teaching effect of the teaching model which is put forward in this paper.

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