

Optimization of English Teaching Mode in Colleges and Universities Based on Deep Learning in the Improvement of Intercultural Communication Skills

Lulu Hao^{1,✉}

¹ School of Foreign Languages, Luoyang Normal University, Luoyang, Henan, 471000, China

ABSTRACT

The application of technologies such as big data, mobile Internet, artificial intelligence and so on has triggered a major change in the field of education and promoted the classroom reform in colleges and universities. Taking deep learning theory as the research perspective, this paper constructs a college English teaching model based on deep learning, and applies the model to actual teaching practice, with a view to promoting students' English learning level and enhancing their intercultural communication ability. Among them, the K-means algorithm improved by the whale optimization algorithm is also used to cluster and stratify the English proficiency of students in a class to illustrate the specific application of deep learning in English teaching. The results classified the sample students into four categories, A, B, C and D. The English level of students in category A is the highest and the largest, accounting for 35.56%, and teachers can design differentiated teaching based on the results of student stratification. After carrying out the experiment of the teaching model, the practicing students' English scores improved by 4.01%, and at the same time, they gained 18.87%~28.45% and 18.82%~39.01% of competence in the personal domain and the communicative domain, respectively, which confirms the effect of the constructed English teaching model on the enhancement of the students' English learning level and cross-cultural communicative competence.

Keywords: deep learning, K-means algorithm, whale optimization algorithm, independent samples t-test, college English teaching

1. Introduction

In today's era of rapid development of information technology, traditional teaching methods are increasingly unable to meet students' learning needs. Especially in the field of English language subjects in colleges and universities, students are faced with various learning difficulties such as

✉ Corresponding author.

E-mail address: haolulu@lynu.edu.cn (L. Hao).

Received 05 February 2024; Revised 12 April 2024; Accepted 05 December 2024; Published Online 15 April 2025.

DOI: [10.61091/jcmcc127a-487](https://doi.org/10.61091/jcmcc127a-487)

© 2025 The Author(s). Published by Combinatorial Press. This is an open access article under the CC BY license (<https://creativecommons.org/licenses/by/4.0/>).

grammar, vocabulary and reading, which is an obstacle to the cultivation of students' intercultural communication skills. In order to improve students' English proficiency and intercultural communication skills, the use of deep learning instructional design has become an important choice [1-2].

Deep learning is an important way of English learning in colleges and universities to cultivate students' language expression and communication skills. The construction of deep learning field is an important direction of the current English teaching reform. By constructing rich and diversified learning resources, designing personalized learning experiences, creating an open learning environment, and carrying out practical learning tasks, it can help students better master English knowledge and skills, and improve students' motivation and learning effect [3-4]. In the English classroom, deep learning should become an educational concept and teaching method, and teachers should actively explore innovative teaching methods to stimulate students' enthusiasm for learning, so that students can experience the fun and meaning of learning in the deep learning field. Schools and education departments should also support and provide training and resource support for English teachers to promote the construction of deep learning field in English classrooms [5-6].

Literature [7] created a university English teaching model and evaluation system based on AI, and evaluated the quality of English speech using DBN. Comparative experiments show that the evaluation model constructed is effective, proving that the AI method can be used in university English education. Literature [8] introduces a hybrid teaching model of university English combining CRF technology and deep learning framework. The research results show that. Compared with traditional teaching methods, the model effectively improves students' English proficiency and comprehension. Literature [9] discussed the changes of college students' English independent learning ability and its influencing factors based on interviews, and predicted and analyzed the weights of the influencing factors using deep neural networks. The findings enrich the theoretical research results of English independent learning ability. Literature [10] studied the theory of deep learning and cited the project-based learning methodology in English teaching in colleges and universities to supplement the theory of deep learning, so as to have some reference value to the teaching mode of colleges and universities. Literature [11] introduces the student emotion recognition method of convolutional neural network, which includes convolutional layer, pooling layer and fully connected layer. It can be applied to create an intelligent learning environment, which provides technical support for improving the realization of emotional interaction and mining learning behaviors. Literature [12] discusses the application of deep learning techniques in English language teaching with the help of stacked logic deep learning. The effectiveness of the enhanced stacked logic deep learning practical teaching method was evaluated through simulation experiments and empirical verification. The results validated its effectiveness. It is emphasized that deep learning technology can effectively improve the teaching effect in English teaching. Literature [13] aims to use deep learning algorithms to optimize the English teaching model and explores the impact of these algorithms on the teaching and learning outcomes of teachers and students. It also provides ideas and methods for the development of English education through empirical studies and case studies. Literature [14] emphasizes the design method of mobile English interactive teaching based on deep learning. Simulation experiments show that the method can effectively improve the dynamic allocation and mining of mobile English interactive teaching resources.

This paper organically combines deep learning and smart classroom construction, using the integration advantages of the two to reshape teaching objectives, integrate teaching resources, innovate teaching methods, optimize teaching evaluation, and construct a college English teaching model based on deep learning. After that, the clustering algorithm is introduced into the English hierarchical teaching, and for the shortcomings of the traditional K-means algorithm, the isolated forest algorithm is used for abnormal data detection, and the whale optimization algorithm is used to select the best initial clustering center. The optimized K-means algorithm is used to analyze the

English proficiency of students in a class in a university, and students with similar characteristics are clustered into one class to realize English tiered teaching. Two classes with similar English proficiency were selected to conduct a teaching experiment, comparing the students' English scores before and after the experiment, as well as the changes in students' competence in multiple dimensions, such as personal and communicative domains, to investigate the effect of the English teaching model on the improvement of the students' English proficiency and cross-cultural communicative competence.

2. A deep learning-based model for teaching English in colleges and universities

The application of deep learning technology can help teaching wisdom generation and promote students' wisdom development. In view of the prevailing problems of ambiguous goals, superficial content, stereotyped teaching and monotonous assessment in the current English teaching in colleges and universities, this study constructs an English teaching model in colleges and universities based on deep learning technology in order to enhance the cross-cultural communicative competence of English students. The content of the college English teaching model is shown in Figure 1, and the implementation of this teaching model is divided into four parts: reshaping goals, integrating resources, flexible teaching and optimizing evaluation.

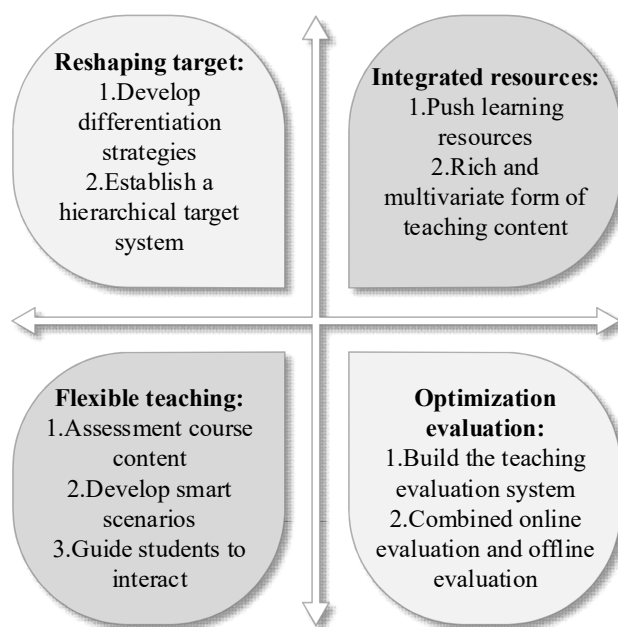


Fig. 1. The content of the English teaching model in colleges

2.1. Reinventing Objectives

To address the problems of vague and shallow teaching objectives, teachers should, on the one hand, combine Bloom's theory of classification of educational objectives, reshape the teaching objectives of English in colleges and universities, analyze the learning situation, and comprehensively grasp the information on the existing knowledge level, learning needs, learning preferences and learning styles through the students' portraits, so that they can establish the starting point of learning for different students, design and adjust the teaching objectives, and formulate differentiated strategies to stimulate the depth of students' learning. Differentiation strategies that can stimulate students' deep learning are formulated. On the other hand, teachers should start from the "three-dimensional" goals of knowledge and skills, process and method, and affective attitude and values, and clarify the six

levels of thinking skills corresponding to different teaching contents, such as facts, abilities, principles, and problem solving, so as to set up a system of goals that goes from the shallow to the deep and progresses step by step. In addition, English teaching should break the traditional curriculum orientation of emphasizing tools rather than humanities, highlighting the objectives of cultivating students' language ability, thinking ability and intercultural competence, and guiding teachers to strengthen students' thinking training through the teaching objectives, so as to give full play to the effectiveness of the curriculum in educating people and realizing the goal of cultivating morality and nurturing people.

2.2. Integration of resources

In view of the prevailing problems of teaching content superficiality and multi-language and less culture in current higher vocational English, on the one hand, it is necessary to rely on the massive and authoritative resource base and accurate platform big data statistical analysis to push appropriate learning resources to students, and pay attention to the introduction of Chinese and Western culture, English and American literature and other related novel knowledge to comprehensively mobilize the students' interest in learning, and to promote students' entry into the state of in-depth learning under the support of rich resources, and to improve students' intercultural competence. On the other hand, teachers should give full play to the advantages of the technical means of the smart classroom, not only to use pictures, audio, animation and other rich and diversified forms to present the teaching content, but also give full play to the advantages of the intuition and vividness of the video teaching, and display the English language as vividly as possible from different perspectives of the story narration type, the interview program type, and the question and discussion type, so as to accurately transmit the knowledge points to the students, and to help the students complete the deep processing, thinking and internalization of the knowledge. This will help students to complete the in-depth processing, thinking and internalization of knowledge, and then improve the teaching effect.

2.3. Flexible teaching

In order to solve the problems of stereotyping, strong memorization and weak thinking in traditional English teaching, on the one hand, teachers should make use of data mining and deep learning methods to comprehensively assess the effectiveness of the course content and the students' learning process, and actively develop intelligent scenarios that are interesting, exploratory and expansive, such as problematic scenarios, task scenarios, and virtual learning scenarios, etc., so that vivid scenarios can attract the attention of the students, activate their learning experience, and promote their high emotional engagement and participation in the activities, and then establish a meaningful connection between the original knowledge and the new knowledge to complete the transfer and application of the knowledge. The vivid scenarios attract students' attention, activate their learning experience, promote their high emotional engagement and participation in the activities, promote the dispersion of thinking, and then establish a meaningful connection between the original knowledge and the new knowledge to complete the transfer and application of knowledge. On the other hand, teachers should adhere to the student-centered approach, design challenging teaching activities, guide students to deeply participate in teaching interactions, combine the support of tools such as Thinking Maps, independently complete the independent inquiry and diagnosis of learning conditions, and improve students' critical thinking skills and their ability to apply knowledge.

2.4. Optimization of evaluation

In order to adapt to the deep learning mode of English teaching, on the one hand, teachers should focus on the three links of the college English classroom before, during and after class, and on the

basis of data analysis, combine the characteristics of the discipline, incorporate the four core literacies of language proficiency, cultural awareness, quality of thinking, and ability to learn, and refine and construct a comprehensive, systematic and dynamic teaching evaluation index system. On the other hand, teachers should pay attention to the organic combination of online and offline evaluation, combining the data of students' learning behaviors, preferences, and hours on the learning platform to evaluate the depth, attitude, and effect of students' independent learning in the process, and combining the completion and correctness of students' self-assessment questions, post-class exercises, and their performance in the offline classroom to conduct the outcome evaluation, and leading the students to reflect through multiple evaluations. Students will be led to reflect through multiple evaluations.

3. Deep Learning-based Tiered Teaching of English Language

In the above discussion of the English teaching mode in colleges and universities, deep learning technology can be used to analyze student portraits so as to develop differentiated teaching strategies. Based on the clustering algorithm in data mining, this chapter explores its practical application in the tiered teaching of English in colleges and universities. Stratified teaching is the process by which teachers scientifically divide students into several groups of similar levels and treat them differently according to their existing knowledge, ability level and potential tendency, and these groups get the best development and improvement from the teachers' appropriate stratification strategies and interactions.

3.1. *K-means algorithm based on whale optimization*

3.1.1. K-means clustering. By clustering, we mean that given a set D , an algorithm is used to divide the elements of D into k subsets such that the dissimilarity between elements in each subset is as low as possible, and the dissimilarity between elements in different subsets is as high as possible; each subset is called a cluster. Clustering is a type of unsupervised learning in which the algorithm mines the data for implicit information for clustering on its own without knowing the categories and the number of categories. Clustering currently has a large number of applications in statistics, biology, database technology, marketing, etc.

K-mean clustering algorithm is an iterative clustering method that utilizes distance as a similarity metric, and it is one of the top 10 most representative data mining algorithms. Simply put, K-mean clustering is to artificially select k elements as the initial clustering center according to a certain strategy without any supervisory information, and then assign the remaining data to the cluster closest to it, i.e., all the elements will be divided into k clusters to complete the division once. However, this k -class is not necessarily the best division, so it is necessary to recalculate the new center point of each class, and then re-divide according to the distance, repeated until the class center remains unchanged. In practice, even after many iterations, the clustering center may still change, so it is often necessary to set a maximum number of iterations, in the iteration number reaches the maximum to stop the calculation.

K-means clustering algorithm is generally divided into two steps: the first step is iteration, calculate the distance between each sample point, and then divide the corresponding sample point into the cluster with the closest distance to complete the initial clustering. The second step is relocation, recalculate the clustering center of each cluster, and divide the closest sample points into the corresponding clusters, and repeat this operation until the clustering center does not change. The algorithm is to obtain the clustering results by means of multiple iterations. The basic idea is: firstly, K initial clustering centers are randomly selected in the given data set. Then calculate the distance of all the sample points, and divide the sample points into the corresponding clusters according to the principle of nearest distance. The clustering centers of the clusters are recalculated

during each iteration. When the clustering center no longer changes or reaches the specified conditions, no more clustering is performed, and then the clustering ends and the clustering results are output.

The average sample distance for dataset D is denoted as:

$$MeanDist(D) = \frac{1}{C_n^2} \sum_{i=1}^n \sum_{j=1}^i d(x_i, x_j) \quad (1)$$

where n is the number of sample points in data set D , C_n^2 is the number of all optional combinations of two randomly selected sample points out of n , and $d(x_i, x_j)$ denotes the Euclidean distance from sample point x_i to sample point x_j .

The sum of error squares for data set D is denoted as:

$$SSE = \sum_{i=1}^k \sum_{x \in c_i} d(x, c_i)^2 \quad (2)$$

where K is the number of clusters, c_i is the clustering center of the i rd cluster C_i , and $d(x, c_i)$ refers to the dissimilarity between data points x and c_i . Different computations of dissimilarity often lead to different clustering results, and here the Euclidean distance metric is usually used. The size of SSE can indicate how dense the sample points are.

3.1.2. Whale Swarm Optimization Algorithm. The whale swarm algorithm is an optimization algorithm that mimics the collective behavior of humpback whales in the ocean for solving the global optimal problem, which mainly consists of three phases: exploration, migration and convergence.

1) Exploration phase. Whales conduct extensive search for prey in the space through random search strategy, the prey is the optimal solution required by the algorithm, the core objective of this phase is to maintain diversity, the mathematical model is as follows:

$$X(t+1) = X_i(t) - AD \quad (3)$$

$$D = |CX_i(t) - X(t)| \quad (4)$$

where D is a random vector, $X(t)$ and $X_i(t)$ denote the position of the current iteration moment t and the optimal position, respectively, A is a scaling factor, and C is a vector of coefficients, which can be expressed as follows:

$$A = 2a\vec{\gamma}_1 - a \quad (5)$$

$$C = 2\overline{\vec{\gamma}_2} \quad (6)$$

where the random vectors $\vec{\gamma}_1$ and $\vec{\gamma}_2$ both take the value range of $[0,1]$. In this phase, the whale moves in a random direction and the scaling factor controls the movement step size.

2) Migration phase. The whale adjusts its position according to the fitness value and realizes rotational movement by decreasing the value of a . The spiral movement of the whale can be expressed by the following equation:

$$X(t+1) = D'e^{bl} \cos(2\pi l) + X'(t) \quad (7)$$

$$D' = |X'(t) - X(t)| \quad (8)$$

where l is a random number between $[-1,1]$, b is a logarithmic constant, and D' denotes the distance between the prey and the whale.

3) Convergence stage. The core objective of this phase is to find out the local optimal solution, and its mathematical model can be expressed as:

$$X(t+1) = X_i(t) - A|CX_r(t) - X(t)| \quad (9)$$

where $X_i(t)$ denotes the global optimal position and $|CX_r(t) - X(t)|$ is a random vector, the model makes the whale search locally in the direction of the global optimal solution.

3.1.3. Overall optimization of the K-means algorithm:

1) Data set sub-domain processing. Generally the dataset will contain multiple features, prioritize the features with higher correlation to the target variable and lower correlation to other features, construct the isolated forest model and set the number of trees and the proportion of abnormal samples. Model training is performed to separate the data with abnormal scores to improve the accuracy and robustness of clustering.

The dataset contains N data point and t isolated trees are constructed, for data point x , the path length on each tree is defined as $h(x, t)$, which represents the number of splits from the root node to data point x . By calculating the path length of a data point on each isolated tree, the isolation measure of the point can be obtained, which is usually expressed by the average path length APL, as shown in equation (10):

$$APL(x) = 2 \frac{E(h(x, t))}{c(N)} \quad (10)$$

where $E(h(x, t))$ denotes the sum of the path lengths of data point x over all isolated trees, and $c(N)$ is the adjustment factor for the average path length, which is represented by equation (11):

$$c(N) = 2(\ln(N-1) + r) - \frac{2(N-1)}{N} \quad (11)$$

where r is the similarity correction factor, the value range is roughly $[0.577, 0.693]$. By calculating $APL(x)$, we can get the scoring value that is inversely proportional to the degree of isolation; the shorter the path length, the higher the scoring value, indicating that the data is more outlier and is most likely to be an anomaly.

2) Intelligent initial clustering center selection strategy. In order to avoid falling into the local optimum, a new clustering center selection strategy is proposed by adopting k-means combined with whale optimization algorithm. Each whale is regarded as an initial clustering center, and its position is expressed as a vector containing multiple clustering centers, and the position in the solution space is evaluated by calculating the fitness function, the specific implementation steps are as follows:

Input: dataset X (data matrix with n samples and m features), number of clustering clusters K , maximum number of iterations max_iter, number of whales num_whales.

Output: optimal initial clustering center best_whale.

Step1: Initialize whale positions to form clusters.

Step2: Calculate the fitness function value $fit(X_i)$ for each whale using the intra-cluster sum of squares as the fitness function.

Step3: Based on the fitness function value, adjust the whale position according to equations (3) and (4).

Step4: Repeat Step2, 3 until the specified number of iterations is reached.

Step5: Select the position with the minimum fitness function value from all whales as the optimal initial clustering center output.

The overall optimization flow of the k-means algorithm is shown in Fig. 2, which uses the state in the Flink computational framework to save the position and fitness value of the whales in each round to avoid frequent data transmission, and the whole iteration process involves many intermediate states, which are regularly saved to the checkpoint using Checkpoint, which can avoid data loss due to the interruption of computation.

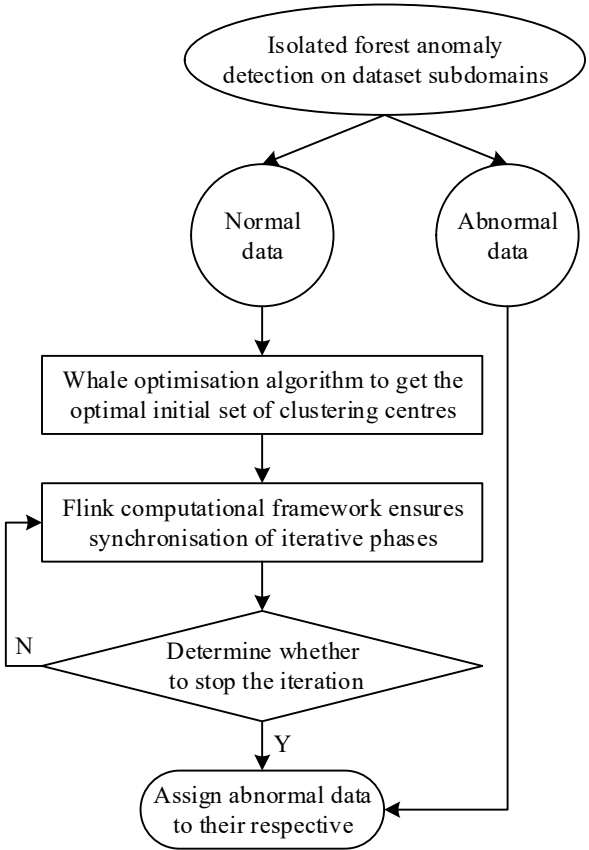


Fig. 2. The overall optimization process of the k-means algorithm

3.2. Case Application Analysis

3.2.1. Data sources. In this paper, a class (45 students) of a university in the first semester of freshman English final grades (including each student's score for each test question with the total score) is selected as the research data, and none of the 45 students' grades have missing values (no grades). The 45 students' scores of each test question (20 questions in total) and the total score were used as the research data, and the results were analyzed in combination with the K-means clustering algorithm based on whale optimization.

3.2.2. Data pre-processing. In order to analyze and evaluate students' performance more scientifically, standardized preprocessing of English performance is needed. The standardized data will not change the degree of mutual influence between the indicators, which very cleverly highlights the difficulty of each test question and students' English proficiency performance, and at the same time eliminates the influence of the full-score scale between each test question, which not only makes the performance of proficiency levels of different test questions comparable, but also improves the speed of convergence of the model and the accuracy of the model. This paper adopts the most widely used standardized data processing method in data analysis: the Z-Score standardization. The Z-Score standardization function is:

$$x_{new} = \frac{x - \mu}{\sigma} \quad (12)$$

where μ is the mean value of the sample data and σ is the standard deviation of the sample data. After the standardized treatment of the sample data, it can not only solve the problem of differences in the original data scale and dimension, but also fully reflect the contribution of different features of the original data to the sample, which can substantially improve the accuracy of data analysis.

3.2.3. Analysis of results. According to the clustering analysis of the students' answers in the test paper, the most appropriate way of grouping students can be calculated, and at the same time, the students corresponding to each weak knowledge point can be clarified and the commonalities and differences in the mastery of English knowledge points of different groups of students can be understood. According to the elbow rule, the optimal number of clusters was selected as 4, i.e., students were divided into 4 layers. In order to observe each category more intuitively, it was first downscaled, and then a scatter plot of the clustering results was produced, and the scatter distribution of the sample students is shown in Figure 3. The clustering process can be seen as a process of "stratification" based on students' English performance, which groups students with the closest performance and the most similar structure together. This can be visualized in the scatter plot of the clustering results, i.e., the students in each category are similar within categories and different between categories. The largest number of students in category A is 35.56%, followed by 28.89% of students in category C, and 20% and 15.56% of students in categories B and D, respectively. The high number of students in categories A and C and the low number of students in categories B and D reminds teachers that they should take early measures to avoid polarization of students' performance.

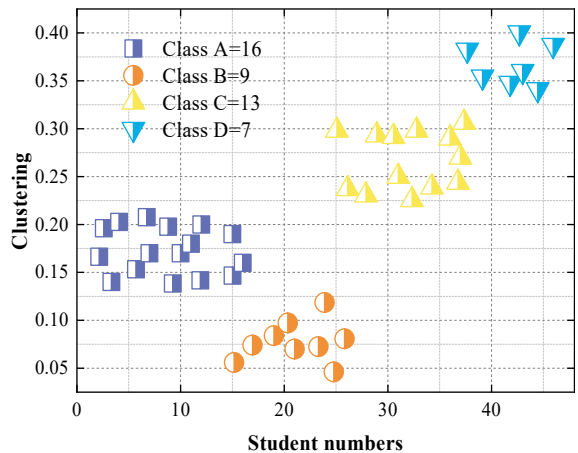


Fig. 3. Sample student divergence distribution

The clustering centers of each test question for each category of students are shown in Table 1. The results of the clustering centers of the four categories of students correspond to [0.52, 0.95], [0.03, 0.48], [-0.48, -0.09], [-0.99, -0.51], based on the results of the clustering centers, combined with the usual English scores of the students in each category, it can be concluded that the English subject competence of the students in each category is in the order of Category A > B > C > D, i.e., the students in Category A are the most excellent. After comparing and analyzing with the usual results, the clustering results are in line with the actual situation.

Table 1. Cluster centers of various students' questions

Topic number	Cluster result
--------------	----------------

	A	B	C	D
1	0.83	0.31	-0.14	-0.99
2	0.78	0.16	-0.28	-0.64
3	0.61	0.45	-0.44	-0.78
4	0.69	0.13	-0.11	-0.53
5	0.64	0.41	-0.41	-0.74
6	0.71	0.42	-0.21	-0.58
7	0.55	0.22	-0.27	-0.78
8	0.68	0.39	-0.09	-0.98
9	0.81	0.21	-0.35	-0.54
10	0.52	0.29	-0.43	-0.96
11	0.72	0.05	-0.27	-0.82
12	0.68	0.22	-0.19	-0.85
13	0.72	0.24	-0.13	-0.57
14	0.79	0.03	-0.26	-0.51
15	0.72	0.37	-0.37	-0.83
16	0.84	0.23	-0.41	-0.65
17	0.59	0.17	-0.43	-0.75
18	0.73	0.35	-0.37	-0.71
19	0.72	0.15	-0.48	-0.66
20	0.95	0.48	-0.25	-0.91

In order to visualize the problem solving ability of students in each category in various question types, the distribution of the ability of students in each category in each question type was plotted, and the ability of students in each category in each question type was shown in Fig. 4, including the distribution of the scores of Listening, Multiple Choice, Completion Fill in the Blanks, Reading, Writing and Total Score. The students of category A excelled in English reading questions and their proficiency in all types of questions was above 0.45. The students of category B and C had shortcomings in English writing with proficiency values of only 0.31 and 0.27. Students in category D scored mainly from single choice questions, which is consistent with the characteristic that the first few questions of a single choice are simple enough to be scored. The overall proficiency values of English for category D students in categories A, B, and C were 0.52, 0.45, 0.35, and 0.28. Teachers should use the results of the cluster analysis as a reference basis to carry out targeted layered English teaching for all types of students, to meet the learning needs of students at different levels of ability, and to stimulate students' learning initiative and motivation.

Based on the current ability level of students at each level, and in conjunction with the teaching objectives, different levels of progressive teaching questions are designed to promote the development of the thinking of students at different levels. For example, simpler questions are answered by class D or class C, and more difficult questions are answered by class B or class A. In order to further consolidate the effect of hierarchical teaching, teachers can also extend it to after-school sessions. For example, when assigning homework, for different levels of students to arrange different levels of difficulty of homework, that is, in addition to doing the necessary basic questions, improve the questions of class A students, but also to do some difficult problems and innovative questions; B, C two types of students in addition to doing the basic questions, but also need to be arranged to improve some of the questions in order to promote the development of their thinking. D students need to do only some basic questions.

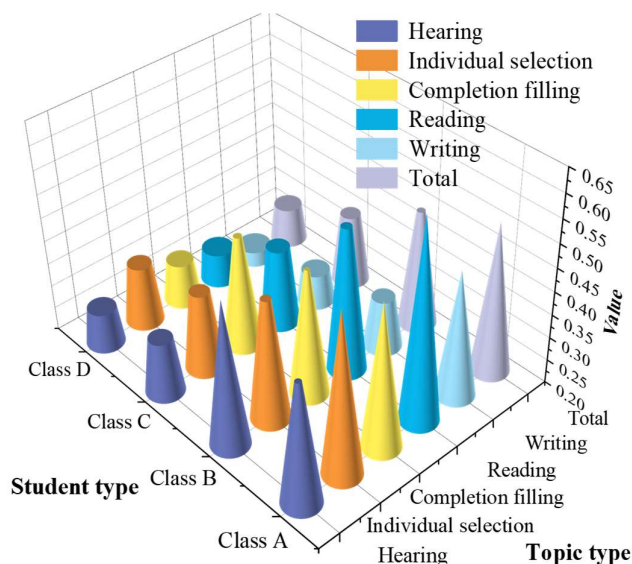


Fig. 4. The problem-solving ability of all kinds of students

4. Effectiveness of improving students' intercultural communication skills

According to the deep learning-based English teaching model in colleges and universities, the application of English classroom teaching is carried out and the effect of students' intercultural communicative competence enhancement under this teaching model is explored.

4.1. Experimental design

The study was conducted with freshmen students in a university, using the experimental-control method, in which two classes of the same grade with similar levels of English learning were selected to conduct the experiment, with Class A (52 students) as the experimental class and Class B (51 students) as the control class. Class A (52 students) was taken as the experimental class and class B (51 students) as the control class. The control class was still taught in the traditional way, while the experimental class was taught in the deep learning-based college English teaching model designed in this paper, in order to verify the effect of the students' English learning and the improvement of their cross-cultural communication skills.

4.2. Experimental tools

1) Questionnaire. In order to further test the effectiveness of the English teaching model based on deep learning in practice, this paper conducted a questionnaire survey on students in Class A before and after class. The questionnaire was designed to test and evaluate the students' English learning level and intercultural communication skills in two dimensions: the personal domain was divided into five secondary dimensions: independent learning, critical thinking, problem solving, creative thinking and transferable thinking, and the interpersonal domain was divided into three secondary dimensions: effective communication, cooperation and cultural knowledge.

2) Pre-test and post-test. As to whether the college English teaching model based on deep learning can improve the English intercultural communication skills of students in the experimental class, a test was administered, which consisted of two sets of papers, i.e., a pre-test paper and a post-test paper. The test consists of two sets of papers, i.e. the pre-test and post-test. Both papers have a total score of 100 points and the test time is 120 minutes. The question types and difficulty coefficients of the two sets of test papers were similar to ensure the authenticity of the data. Both classes were tested before and after the experiment and the test results were compiled. Finally, the data results

were analyzed with SPSS 24.0 software, with the purpose of testing whether the college English teaching model based on deep learning can improve students' English proficiency and intercultural communication skills.

4.3. Analysis of the effects of implementation

4.3.1. Analysis of student performance. In order to ensure the authenticity and validity of the achievement test, the study chose to compare the results in Class A and Class B. Before the implementation of the two classes, the two classes have the same level of performance in the monthly examination, the same teaching progress and the same teachers, after the model practice in class A, the study collected and counted the results of the monthly examination of the two classes, after the completion of the data collection, the statistical analysis of the students' performance in the pre and post-tests was conducted, the data were analyzed by using the independent samples t-test with the SPSS 24.0, and the results of the analysis of the data of the pre and post-tests of the students were as follows in Table 2. The results of the students' pre and post-tests are shown in Table 2.

Pre-test: to carry out independent samples t-test, first of all, the independent samples should be tested for chi-square, $F = 0.851$, Sig is 0.627 greater than 0.05, so the two samples are chi-square, independent samples t-test can be carried out, P is 0.568 greater than 0.05, so there is no significant difference in the English scores of the two classes.

Post-test: the same independent sample t-test is conducted on the data results, first of all, the variance chi-square test is conducted on the independent samples, F is 0.032, Sig is 0.422 is greater than 0.005, so the two samples are chi-square and can be subjected to the independent sample t-test, $P = 0.006 < 0.05$, so there is a difference in the English scores of the two classes, and the mean of class A is slightly higher than the class B's mean value, indicating that the implementation of the college English teaching model based on deep learning is effective. Among them, the English scores of the students in class A were 4.01% higher than those of class B, and 7.51% higher than those before the experiment.

Table 2. Data analysis results before and after students' test

Class	Before experiment		After experiment	
	Class A	Class B	Class A	Class B
Number	52	51	52	51
Mean	53.55	54.59	57.57	55.35
SD	5.24	6.06	4.38	5.31
t	-2.45	-2.27	1.16	1.28
p	0.568	0.568	0.006	0.006

4.3.2. Analysis of questionnaires. Pre- and post-test questionnaires were administered to the students in Class A. The collected data were cleaned, organized and imported into SPSS, and the sample data were normally distributed can be subjected to independent sample t-test. This study analyzes the learners' English language proficiency and cross-cultural communicative competence around two aspects, one of them is to analyze the personal domain, and the other is to analyze the interpersonal domain.

The results of the analysis of the pre- and post-test questionnaires are shown in Table 3. The mean scores of the post-test of the overall level of English learning of the students in Group A are higher than those of the pre-test, and there is a significant difference ($p < 0.01$). In the data analysis of the eight aspects of this questionnaire, namely, independent learning, critical thinking, creative thinking, problem solving, transfer thinking, effective communication, cooperation ability and cultural knowledge, all of them showed different degrees of improvement, with the personal and communicative domains improving by 18.87% to 28.45% and 18.82% to 39.01%, respectively.

Therefore, the English proficiency and intercultural communicative competence of the study participants were promoted under this teaching model.

Table 3. Analysis of questionnaire survey before and after experiment

Dimension		Type	Mean	SD	Sig.	Sig. (Double tail)
Personal domain	Autonomous learning	Before	3.51	0.55	0.006	0.004
		After	4.26	0.42		
	Critical thinking	Before	3.61	0.39	0.009	0.005
		After	4.37	0.22		
	Creative thinking	Before	3.43	0.46	0.008	0.001
		After	4.35	0.39		
	Problem solving	Before	3.48	0.58	0.002	0.000
		After	4.47	0.41		
	Migration thinking	Before	3.55	0.46	0.008	0.006
		After	4.22	0.38		
Communication area	Effective communication	Before	3.23	0.36	0.006	0.004
		After	4.49	0.24		
	Cooperative ability	Before	3.56	0.39	0.003	0.001
		After	4.23	0.26		
	Cultural knowledge	Before	3.38	0.61	0.005	0.002
		After	4.49	0.51		

5. Conclusion

The development of intelligent technology has increased the teaching breadth for English teaching in colleges and universities. Based on the theory of deep learning, this study constructs a college English teaching model based on deep learning based on the improvement of students' intercultural communication ability. Using the K-means algorithm based on whale optimization, we analyze the application of data mining technology in English hierarchical teaching. Then implement the teaching experiment to explore the effect of the proposed teaching mode on the improvement of students' intercultural communicative competence.

1) The sample students are divided into four types of A, B, C and D through cluster analysis, accounting for 35.56%, 28.89%, 20% and 15.56% respectively, and their English proficiency decreases in this order, with the overall English proficiency level corresponding to 0.52, 0.45, 0.35 and 0.28. Teachers can design different teaching objectives and contents according to the different levels of students. Teachers can design different teaching objectives and teaching contents according to different levels of students, and conduct English classroom teaching according to the students' abilities.

2) After applying the English teaching model based on deep learning, the students in class A have a 4.01% higher English achievement than the students in class B. At the same time, there is a significant difference between the pre-experiment and the experiment in the areas of independent learning, critical thinking, innovative thinking, problem solving, transferable thinking, effective communication, cooperative ability and cultural knowledge ($p < 0.01$), and the competence in the personal domain and the communication domain has been increased by 18.87%~28.45% and 18.82%, respectively. 28.45% and 18.82%~39.01% respectively.

Deep learning-based English teaching in colleges and universities has deeply changed the traditional English classroom teaching mode, helping teachers grasp the learning situation more comprehensively, reflect on their teaching in time, optimize the teaching design, and improve the deep teaching ability and the effect of English teaching. In addition, it also mobilizes students' enthusiasm for English learning and cooperative communication ability, enhances their critical thinking and problem solving ability, and improves their cross-cultural communication ability.

References

- [1] Luo, J., & Garner, M. (2017). The challenges and opportunities for English teachers in teaching ESP in China. *Journal of Language Teaching and Research*, 8(1), 81.
- [2] Wette, R., & Barkhuizen, G. (2009). Teaching the book and educating the person: Challenges for university English language teachers in China. *Asia Pacific Journal of Education*, 29(2), 195-212.
- [3] Jiang, R. (2022). Understanding, Investigating, and promoting deep learning in language education: A survey on chinese college students' deep learning in the online EFL teaching context. *Frontiers in Psychology*, 13, 955565.
- [4] Shi, J. (2022). Deep Learning for College English Education Evaluation. *Mobile Information Systems*, 2022(1), 3558558.
- [5] Xu, J., Liu, Y., Liu, J., & Qu, Z. (2022). Effectiveness of English online learning based on deep learning. *Computational Intelligence and Neuroscience*, 2022(1), 1310194.
- [6] Sun, G. (2024). Research on the Intelligent System of English Teaching from the Perspective of Intercultural Education Based on Deep Learning. *International Journal of High Speed Electronics and Systems*, 2440107.
- [7] Wu, F., Chen, Y., & Han, D. (2022). Development countermeasures of college english education based on deep learning and artificial intelligence. *Mobile Information Systems*, 2022(1), 8389800.
- [8] Feng, H. (2024). A Blended Teaching Model of College English Based on Deep Learning. *Journal of Electrical Systems*, 20(6s), 1505-1515.
- [9] Chang, H. (2021). College English flipped classroom teaching model based on big data and deep neural networks. *Scientific Programming*, 2021(1), 9918433.
- [10] Han, L. (2023). A Practical Study of Project-based Learning Approach Pointing to Deep Learning in College English Teaching. *International Journal of New Developments in Education*, 5(20).
- [11] Zhang, D. (2022). Affective cognition of students' autonomous learning in college English teaching based on deep learning. *Frontiers in psychology*, 12, 808434.
- [12] Shi, Z., & Yang, Y. (2024). Application of Deep Learning Technology in English Practical Teaching. *Journal of Electrical Systems*, 20(3s), 1897-1906.
- [13] Yun, W., Zhu, J., & Wu, T. (2024). Optimization of English Teaching Model Based on Deep Learning Algorithm. *International Journal of High Speed Electronics and Systems*, 2440098.
- [14] Yan, Z., Bing, Y., & Shimeng, P. (2024). Interactive teaching design of mobile English based on deep learning. *Journal of Ambient Intelligence and Humanized Computing*, 1-14.