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A Strategic Study on Improving the Quality of College English Teaching through Computational Analysis of Learning Behavior

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Abstract The development of education informatization has given rise to a large amount of learning behavior data, which provides new ideas for education management and teaching quality improvement. This paper constructs a learning behavior computational analysis model based on the XGBoost algorithm and explores the strategies for improving the quality of college English teaching. Starting from students' English learning behavior data, the study extracts six features: speaking practice, English writing, English classroom homework, consulting English dictionary, memorizing English words, and English listening practice, and establishes a computational analysis model through data preprocessing and feature engineering. The results show that the XGBoost algorithm performs well in the computational analysis of learning behaviors, with an accuracy of 0.9592, a recall of 0.9644, and an F1 value of 0.9618, which is significantly higher than that of traditional machine learning methods. Teaching experiment validation shows that the teaching strategy formulated based on the results of computational analysis can effectively improve the quality of teaching, and the average value of students' English performance in the experimental group improves from 62.33 points in the pre-test to 88.08 points in the post-test, which is significantly higher than that of the control group, which is 63.81 points. The post-test questionnaire showed that the strategy use level of students in the experimental group increased from "low-moderate" to "high" before the intervention. The study proposes teaching strategies such as constructing an ecological classroom, implementing behavioral preventive measures, and creating an English teaching environment, which provide theoretical basis and practical guidance for improving the quality of college English teaching.

Index Terms Learning Behavior, Computational Analysis, College English, Teaching Quality, XGBoost Algorithm, English Teaching Strategies

I. Introduction

College English teaching has become a widely concerned course in the teaching process of Chinese college students, and it also plays an increasingly important role in the employment of college students [1]. For college students, only by mastering a better level of English can they be better adapted to their future work and the trend of economic globalization [2]. From the current development of college students' English teaching, the factors affecting the quality of college students' English teaching are manifold. In view of these influencing factors, it is the general trend for the development of university English education to formulate reasonable and effective countermeasures to further promote the improvement of the quality of university English teaching.

At this stage, scholars at home and abroad focus on the teaching evaluation of English courses in terms of the construction of evaluation index system, evaluation models and methods [3], [4]. As most of the evaluation methods only rely on students' usual grades and final exam results, ignoring the intrinsic connection between students' learning behaviors and learning effects in the learning process, the evaluation results are one-sided [5]-[7]. And on the whole, the research on the evaluation of English course teaching pays more attention to the evaluation of learning effect, while the research on the evaluation of teaching quality is relatively less, especially on how to use students' learning behavior and preference to implement the evaluation of course teaching quality is rarely researched [8]-[11]. Then, whether students' learning behaviors and preferences can be used as decision-making attributes and computational analysis methods can be used to obtain real-time evaluation results of teaching quality, so as to improve and optimize teaching strategies in a timely manner, is a research issue of great value [12]-[14].

The quality of English teaching in higher education has always been a key area of concern in educational research and practice. As a public basic course in colleges and universities, the quality of college English teaching has a direct impact on the development of students' language ability and their future career development. However, traditional college English teaching often suffers from problems such as emphasizing the results but neglecting the process, and the mismatch between teaching strategies and students' needs, resulting in unsatisfactory teaching results. The development of educational data mining and learning analytics technology provides new methods and perspectives for teaching quality improvement. Through the collection, cleaning and analysis of students' learning behavior data, we can gain insight into students' learning process, preferences and difficulties, thus providing data support for teaching decisions. The application of machine learning algorithms in education has shown great potential, especially in predicting learning outcomes, identifying learning patterns and optimizing teaching strategies.XGBoost, as a highly efficient and integrated learning algorithm, has significant advantages in dealing with complex feature relationships and improving prediction accuracy. Under the background of the deep integration of information technology and education and teaching, how to use advanced computational analysis methods to parse students' learning behavior data and transform the analysis results into effective teaching strategies has become a key issue to improve the quality of university English teaching.

This study starts from students' English learning behavior data, constructs a computational analysis model based on XGBoost, and digs deeper into the correlation between learning behavior and learning effect. First, the original data are preprocessed to extract key learning behavior features; second, the model hyperparameters are set and optimized to establish a high-precision computational analysis model of learning behavior; then, the model is compared and verified with other machine learning algorithms to prove its superiority in learning behavior analysis; finally, the targeted teaching strategies are formulated based on the results of the analysis, and the effectiveness is verified through experiments. By combining data science methods with educational teaching practice, we aim to provide theoretical basis and practical guidance for the improvement of the quality of university English teaching, and at the same time explore new paths for the application of educational data mining in the field of language teaching.

II. English Teaching Strategies Based on Computational Analysis of Learning Behavior

II. A.Research data

With the development of education informatization, a large amount of data has been generated from various learning behaviors of students. In order to bring the data into play, the use of machine learning algorithms to explore and utilize the value embedded in educational data has become the focus of research scholars. The emergence of massive data provides a large amount of potential value for educational administrators, which helps to improve the management efficiency of administrators. Educational administrators can coordinate the planning based on students' English learning behaviors, start from the management of teaching methods and the management of teaching modes, improve the management level, and provide early warnings for the quality of university English teaching. According to the specific situation of university English teaching, suggestions are made for the specific implementation of their learning behaviors, aiming to improve the quality of university English teaching.

II. A. 1) Data pre-processing

In order to play the xgboost algorithm for learning behavior computational analysis, it is first necessary to preprocess the data, including data collection, data cleaning, data integration and data transformation processes.

Data collection means that multiple databases receive data from clients, and users are able to find and process the work simply through these databases. Traditional relational databases such as MySQL, Sql server, and Oracle are used to store basic data of teachers and students, course data, etc.

Data cleansing is done by completing the missing values, processing the noisy data, commonly used mean value to fill the missing values, nowadays data cleaning methods focus on enhancing the interactivity with each other.

Data integration gathers data from multiple data sources and stores them in one and the same data store. Data from the data center is merged and processed according to the specific business, and according to the business requirements and permission information, the central database data is reorganized to generate business database tables, and services are provided to the outside world through interfaces and views to ultimately achieve data sharing.

Data transformation unifies the data into a suitable form for mining.

II. A. 2) Feature extraction of the dataset

The original data comes from various departments in the school, and the data from the Academic Affairs Office and other departments provide data such as daily learning behaviors. The features needed for algorithm model training are extracted from these datasets, and the features include English Walkman, note taking, reading aloud English materials, speaking practice, English writing, English classroom homework, listening to English songs, memorizing English words, consulting English dictionaries, watching British and American movies and TV, and English listening practice, and there are 1,246,132 pieces of data in the original summary table dataset of students' English learning behaviors. Using the merge function of the pandas library to connect the data according to the xh field, various features are integrated, and finally six features are extracted, namely, oral practice, English writing, English classroom homework, consulting the English dictionary, memorizing English words, and English listening practice.

II. A. 3) Label classification of data sets

The following is a statistical table of learning behaviors of students graduating in 2020-2024 with 13,680 data, and the categories of students' English learning behaviors include six characteristics: oral practice, English writing, English classroom work, consulting the English dictionary, memorizing English words, and English listening practice.

II. A. 4) Experimental description of the data set

The data first needs to be pre-processed, including the processes of data cleaning, data integration, and data integration. The pandas library in python is used to remove duplicate values, fill in missing values, integrate features and labels of the data, and finally form 6 tables of speaking practice, English writing, English classroom homework, consulting English dictionary, memorizing English words, and English listening practice. The features include six feature cases of speaking practice, English writing, English classroom homework, consulting English dictionary, memorizing English words, English listening practice, and failing subjects in the second semester, and the labels are categorized into speaking practice, English writing, English classroom homework, consulting English dictionary, memorizing English words, and English listening practice.

II. B.XGBoost-based computational analysis model for learning behavior

II. B. 1) XGBoost Algorithm

Extreme Gradient Boosting (XGBoost) is an integrated learning algorithm that improves and extends on the Gradient Boosting Tree algorithm [15], [16]. The main process of its modeling is to predict the dataset by constructing multiple CART models, and finally to form a new tree model by integrating multiple tree models [17]. Since a new tree model is generated by iterating continuously based on the residuals of the previous tree, the complexity of the integrated model increases and the deviation of the integrated model decreases as the number of model iterations increases. The tree as an additive model is represented as a function as shown in equation (1):

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F \tag{1}$$

In Eq. (1), $\hat{y}_i$ is the predicted value of the model for the i th sample, K is the number of trees, F is the ensemble space of the trees, and $f_k(x_i)$ is the predicted value for the i th sample in the k th tree.

Where:

$$f_k(x_i) = w_{q(x_i)} \tag{2}$$

In Eq. (2), w is the set of leaf node values in the k th tree, and $q(x_i)$ is the position of the leaf node where the i th sample in the k th tree is located.

Its objective function is:

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{3}$$

In Eq. (3), part 1 is the loss function. Part 2 is the sum of the complexity of the tree.

The complexity of the tree is calculated as shown in equation (4):

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \| w \|^2 = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{4}$$

In Eq. (4), γ and λ are the penalty coefficients of the model, T is the number of leaf nodes, and w_j is the predicted value on leaf node J. Using Boosting method there is $\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i)$. Neglecting the constant term $\sum_{k=1}^{t-1} \Omega(f_k)$, we can get the t times training objective function as shown in equation (5):

$$Obj^{(t)}=\sum_{i=1}^{n}l(y_i,\hat{y}_i^{(t-1)}+f_i(x_i))+\Omega(f_i) \tag{5}$$

Define the first order derivative of the loss function as $g_i=\partial_{\hat{y}_i^{(t-1)}}l(y_i,\hat{y}_i^{(t-1)})$ and the second order derivative as $h_i=\partial^2_{\hat{y}_i^{(t-1)}}l(y_i,\hat{y}_i^{(t-1)})$, and the set of samples on leaf node j is $I_j=\{i\mid q(x_i)=j\}$.

A second-order Taylor expansion of Eq. (6) at $\hat{y}_i^{(t-1)}$ and neglecting the constant term yields:

$$\begin{aligned}Obj^{(t)}&=\sum_{i=1}^{n}l\left(y_i,\hat{y}_i^{(t-1)}+f_t\left(x_i\right)\right)+\Omega\left(f_t\right)\\&\cong\sum_{i=1}^{n}\left[l\left(y_i,\hat{y}_i^{(t-1)}\right)+g_if_t\left(x_i\right)+\frac{1}{2}h_if_t^2\left(x_i\right)\right]+\Omega\left(f_t\right)\\&\cong\sum_{i=1}^{n}\left[g_iw_{q(x_i)}+\frac{1}{2}h_iw_{q(x_i)}^2\right]+\gamma T+\frac{1}{2}\lambda\sum_{j=1}^{T}w_j^2\\&\cong\sum_{j=1}^{T}\left[\left(\sum_{i\in I_j}g_i\right)w_j+\frac{1}{2}\left(\sum_{i\in I_j}h_i+\lambda\right)w_j^2\right]+\lambda\end{aligned} \tag{6}$$

Letting equation (6) be zero and taking partial derivatives with respect to w_j yields equations (7) and (8). i.e:

$$w_j^*=-\frac{\sum_{i\in I_j}g_i}{\sum_{i\in I_j}h_i+\lambda} \tag{7}$$

$$Obj^*=-\frac{1}{2}\sum_{j=1}^{T}\frac{\left(\sum_{i\in I_j}g_i\right)^2}{\sum_{i\in I_j}h_i+\lambda}+\gamma T \tag{8}$$

The optimal solution of the objective function can be obtained when the tree structure is known, by dividing the subtree using the greedy algorithm, calculating the information gain of each split point by enumeration, and selecting the direction with the largest information gain for node splitting. The information gain is calculated as shown in equation (9):

$$L=\frac{1}{2}\left[\frac{\left(\sum_{i\in I_L}g_i\right)^2}{\sum_{i\in I_L}h_i+\lambda}+\frac{\left(\sum_{i\in I_R}g_i\right)^2}{\sum_{i\in I_R}h_i+\lambda}-\frac{\left(\sum_{i\in I}g_i\right)^2}{\sum_{i\in I}h_i+\lambda}\right]-\gamma \tag{9}$$

II. B. 2) Model hyperparameters

The XGBoost algorithm contains many hyperparameters, for example, tree depth, number of trees, learning rate, etc., and the model hyperparameters are shown in Table 1.

Table 1: Model hyperparameters

Hyperparameter	Meaning	Range
n_estimators	The number of trees	The default is 100.
max_depth	The depth of the tree	$[0,\infty]$
learning_rate	Learning rate	The default is 0.1
Subsample	Down sampling	(0,1]
colsample_bytree	List the proportion	(0,1]
min_child_weight	Minimum leaf node weight	The default is 1
Gamma	Minimum loss of leaf node splitting	The default is 0
reg_alpha	L1 regularization term weight	The default is 1
reg_lambda	L2 regularization term weight	The default is 0

max_depth is a hyperparameter used to control the degree of model fitting, in general, when the number of trees in the model is increased, the model learning ability is stronger, in order to prevent the degree of model fitting from becoming weaker, the depth of the tree needs to be taken in a certain range of values. learning_rate is a hyperparameter used to control the step size of the model learning, the learning rate reflects the model's ability to generalize, if the value of the learning rate is taken too If the value of learning_rate is too large, the search step increases during model training, which reduces the training time of the model, and if the value of learning_rate is too small, it increases the training time of the model and reduces the prediction bias of the model. In addition n_estimators, subsample and colsample_bytree hyperparameters also affect the prediction model performance. In summary, the performance of the XGBoost model depends on the hyperparameters n_estimators, max_depth, learning_rate, subsample and colsample_bytree, therefore, when building a computational analysis model of students' English learning behaviors based on XGBoost, these five hyperparameters are chosen as the key optimization parameters of the model.

II. B. 3) Mathematical modeling

The implementation process of the XGBoost-based computational analysis model of students' English learning behavior is similar to that of the RS-RF model, except that the setup of the hyperparameters is different, and the search range and search step size of the hyperparameters are also different. The construction process of the XGBoost-based computational analysis model of students' English learning behavior is as follows:

Step1: The original sample dataset outliers are detected and removed using the method above, and the preprocessed sample dataset is divided into training set and test set, and feature selection is performed.

Step2: Achieve the purpose of dimensionality reduction of auxiliary variables by eliminating irrelevant variables, establish the XGBoost prediction model, set the model hyper-parameter search range and search step for random search, and output the XGBoost optimal hyper-parameters when the number of times of searching for optimality is satisfied.

Step3: Use the output optimal hyperparameters to establish the computational analysis of students' English learning behavior based on XGBoost, conduct computational analysis on the cement data of the training set and the test set, output the results and conduct performance evaluation.

II. C. Developing English Teaching Strategies

II. C. 1) Constructing ecological classrooms

By calculating and analyzing students' serialized learning behaviors with the help of XGBOOST algorithm and giving corresponding evaluations, we can understand the learning situation and track the learning process in time. To promote learning by evaluation, to improve teaching based on evaluation, to improve students' participation and the correlation between learning behavior and performance, to improve students' learning, in order to improve the effectiveness of teaching and to show the results of the classroom, which is beneficial to improve the quality of college English teaching. For example, through the computational analysis of students' learning behaviors, creating a teaching method that is compatible with them, while the intelligent characteristics of information technology carry out the evaluation and monitoring of the whole process of students, which ultimately makes the learning method more targeted, the provision of language materials more personalized, and enhances the maximum efficiency of the language input and output of each learner.

II. C. 2) Behavioral preventive measures

Undoubtedly, the student-centered calculation and analysis of students' serialized learning behaviors using the XGBOOST algorithm can improve the quality of university English teaching, and at the same time, due to the ubiquity of the technology and the degree of self-discipline of the subject of learning, it is necessary to carry out the necessary guidance and monitoring during the process of information technology-assisted teaching, which brings about the need to add the factor of monitoring and feedback in the evaluation system before can make English teaching more scientific. For example, on the “Classroom on the Go” platform of Foreign Teaching Service, students' learning is accurately recorded, including the input, correctness, completion, mastery, learning time and number of attempts for each content block. Teachers can view the learning of their students in real time through the Class Learning Status, which monitors learning in terms of the average correct rate and average progress of the class, the correct rate of each student, the learning time, progress, and Q&A situations. These vital learning data are regularly published weekly or monthly feedback to students, students know themselves and others, with pressure, will produce the effect of advanced to promote the latter.

II. C. 3) Creating an English language teaching environment

The classroom should pay full attention to students' English learning behavior, give full play to students' learning initiative, and students should be allowed to choose online catechism based on their learning behavior. The Academic Affairs Office of the school should formulate relevant teaching management measures, classify online catechism courses as elective courses, monitor students' learning behavior, and arrange teachers to intervene to strengthen counseling. Students can get the corresponding credits after completing the study and passing the examination. For example, in the foreign language catechism platform in colleges and universities, there are many national high-quality online open courses, which bring together high-quality foreign language catechism resources, and can be used as an effective supplement to foreign language teaching in colleges and universities. Like Fun English and Translation, English Talking about China, English Movie Audiovisual Speaking, English Oral Interesting Talk, English Speech Art, etc., many of these courses are novel in form, with rich and interesting contents, combining knowledge and fun, and are three-dimensional courses of sight, hearing and speaking, which can help students improve their language skills and broaden their cultural horizons. The Academic Affairs Office can select certain courses to recommend to students according to the characteristics of their English learning behavior.

III. Validation Analysis of Models and Instructional Strategies

III. A. Model validation analysis

III. A. 1) Setting up the experimental environment

The experimental environment for this topic is built on Ubuntu. Due to the practical environment limitations, this topic only uses one personal computer as the host for building, and three VMware virtual machines running Ubuntu system are installed on this one host, and the VMware virtual machines are connected by NAT. The specific hardware configurations and installed software of the host and virtual machines are shown in Tables 2 to 3. The environment for data analysis in this topic is based on the Ubuntu system on the three VMware virtual machines.

Table 2: Host configuration

Name	Configuration information
Hard disk	512G
Processor	Intel(R) Core(TM)@2.60GHz
Running memory	16G
Operating system	Win10 32 bit
Virtual machine	VMware Workstation 15
Eclipse	Kepler

Table 3: Virtual machine configuration

Name	Configuration information
Operating system	Ubuntu19
Number of CPU cores	4
Memory	8G
JDK	Jdk-2.0.0_151
Hard disk	128G
Hadoop	Hadoop 2.8.8

III. A. 2) Evaluation indicators

On the basis of the experimental environment above, this paper uses confusion matrix to visualize the results of computational analysis of students' English learning behaviors. The concepts of which confusion matrix are as follows:

(1) TP (true positive): the results of the computational analysis of students' English learning behaviors will be true.

(2) TN (true negative): the results of the computational analysis of students' English learning behaviors will be false.

(3) FP (False Positive): the result of the computational analysis of students' English learning behaviors will be false.

(4) FN (False Negative): the result of the computational analysis of students' English learning behavior will be false.

Combining relevant information and literature, Accuracy, Recall, and F1 are used as the evaluation indexes of this study. The specific calculation formula is shown below:

$$Accuracy = \frac{TP}{TP+FP} \times 100\% \tag{10}$$

$$\mathrm{Re}call = \frac{TP}{TP+FN} \times 100\% \tag{11}$$

$$F1 = \frac{2 \times Accuracy \times \mathrm{Re}call}{Accuracy + \mathrm{Re}call} \tag{12}$$

III. A. 3) Analysis of results

RF (Random Senri), DT (Decision Tree), SVM (Support Vector Machine), KNN (K Nearest Neighbor Algorithm), GBDT (Gradient Boosting Decision Tree) are used as control algorithms in this study, and students' English learning behaviors of speaking practice X1, English writing X2, English classroom homework X3, consulting the English dictionary X4, memorizing English vocabulary X5, and listening practice X6 are set as the research data The confusion matrix of different algorithms is shown in Table 4~Table 9, and the results of algorithm evaluation indexes are shown in Table 10. Comprehensive Table 4~Table 10 shows that compared with RF (Accuracy: 0.6291, Recall: 0.6672, F1: 0.6476), DT (Accuracy: 0.7178, Recall: 0.7234, F1: 0.7206), SVM (Accuracy: 0.7335, Recall: 0.7569, F1: 0.7450), KNN (Accuracy: 0.8383, Recall: 0.8477, F1: 0.8430), GBDT (Accuracy: 0.9209, Recall: 0.9315, F1: 0.9662), and the algorithm of this paper (Accuracy: 0.9592, Recall: 0.9644, F1: 0.9618) has a higher priority in the computational analysis of students' English learning behaviors, which can promote the improvement of the quality of university English teaching.

Table 4: Confusion matrix(RF)

Name	X1	X2	X3	X4	X5	X6	Accuracy
X1	0.6569	0.0357	0.1074	0.0723	0.0402	0.0875	0.6291
X2	0.1109	0.6128	0.1063	0.1106	0.045	0.0144	
X3	0.0889	0.1197	0.6838	0.054	0.0272	0.0264	
X4	0.0744	0.0545	0.0206	0.6048	0.0766	0.1691	
X5	0.0271	0.0948	0.0201	0.042	0.6096	0.2064	
X6	0.1598	0.1024	0.0269	0.0835	0.0208	0.6066	

Table 5: Confusion matrix(DT)

Name	X1	X2	X3	X4	X5	X6	Accuracy
X1	0.7048	0.0307	0.0771	0.033	0.0289	0.1255	0.7178
X2	0.0178	0.7077	0.0836	0.0939	0.0331	0.0639	
X3	0.0295	0.0433	0.7466	0.1015	0.0354	0.0437	
X4	0.015	0.093	0.0905	0.7247	0.0356	0.0412	
X5	0.053	0.0527	0.0854	0.046	0.7421	0.0208	
X6	0.0951	0.0547	0.0964	0.0653	0.0075	0.681	

Table 6: Confusion matrix(SVM)

Name	X1	X2	X3	X4	X5	X6	Accuracy
X1	0.7053	0.045	0.0743	0.0345	0.0203	0.1206	0.7335
X2	0.0466	0.7701	0.0518	0.0966	0.0154	0.0195	
X3	0.0383	0.084	0.7281	0.0222	0.0453	0.0821	
X4	0.0102	0.0508	0.0714	0.7936	0.0146	0.0594	
X5	0.0911	0.0799	0.0516	0.0498	0.7229	0.0047	
X6	0.0582	0.058	0.05	0.0755	0.0774	0.6809	

Table 7: Confusion matrix(KNN)

Name	X1	X2	X3	X4	X5	X6	Accuracy
X1	0.8386	0.0754	0.0416	0.0133	0.0167	0.0144	0.8383
X2	0.0206	0.8624	0.0251	0.056	0.0145	0.0214	
X3	0.0198	0.0293	0.8695	0.0462	0.0128	0.0224	
X4	0.0336	0.0206	0.028	0.8071	0.0302	0.0805	
X5	0.0211	0.0216	0.0503	0.0325	0.8516	0.0229	
X6	0.0268	0.0551	0.0215	0.0457	0.0505	0.8004	

Table 8: Confusion matrix(GBDT)

Name	X1	X2	X3	X4	X5	X6	Accuracy
X1	0.9255	0.0088	0.0426	0.0081	0.0033	0.0117	0.9209
X2	0.0097	0.9285	0.0097	0.049	0.0004	0.0027	
X3	0.0293	0.0251	0.9283	0.0094	0.0026	0.0053	
X4	0.0057	0.0043	0.0203	0.9123	0.0033	0.0541	
X5	0.0011	0.0236	0.0097	0.0077	0.9346	0.0233	
X6	0.0086	0.0254	0.0235	0.044	0.0026	0.8959	

Table 9: Confusion matrix(XGBOOST)

Name	X1	X2	X3	X4	X5	X6	Accuracy
X1	0.9551	0.0052	0.0106	0.0025	0.0011	0.0255	0.9592
X2	0.0019	0.9533	0.0042	0.009	0.0064	0.0252	
X3	0.0033	0.0024	0.9723	0.0015	0.0087	0.0118	
X4	0.0015	0.0037	0.0081	0.9651	0.0013	0.0203	
X5	0.0083	0.0027	0.0107	0.003	0.9462	0.0291	
X6	0.0051	0.0085	0.0094	0.0106	0.0033	0.9631	

Table 10: Algorithm evaluation index results

Algorithm	Accuracy	Recall	F1-Value
RF	0.6291	0.6672	0.6476
DT	0.7178	0.7234	0.7206
SVM	0.7335	0.7569	0.7450
KNN	0.8383	0.8477	0.8430
GBDT	0.9209	0.9315	0.9262
XGBOOST	0.9592	0.9644	0.9618

III. B. Validation Analysis of Teaching Strategies

III. B. 1) Objects of study

The experimental subjects of this study choose two classes in a key undergraduate university in a province, namely, Class A and Class B of English majors, with 30 students in each class, in which Class A is the control class and Class B is the experimental class, and in the process of college English teaching, the experimental class will be subjected to the teaching strategies formulated in this paper, while the control class adopts the traditional college English teaching strategies without adding any intervention conditions. This study has been teaching college English to these two classes since the first semester of the freshman year, and the students in these two classes have almost the same level of English. The textbooks they used were the same college English textbooks, and the teachers adjusted the teaching materials and contents according to their teaching needs during the teaching process.

III. B. 2) Research tools

The research instruments of this study include pre-tests, post-tests, questionnaires and student interviews.

(1) Questionnaire Survey

Based on the actual situation in the working area and personal classroom observation, as well as combining relevant research results, this study prepared a Questionnaire on the Current Status of the Use of College English Teaching Strategies, which lists 10 statements related to college English teaching strategies. It aims to confirm the effectiveness of university English teaching strategies based on the computational analysis of student behavior.

(2) Test Method

The pre-test was conducted at the beginning of July 2023, using the college English examination paper of the second semester of the first year of college and the examination scores (out of 100) of the two classes were counted. After the 8-week teaching experiment intervention, the post-test was conducted in early December 2023, using the university English examination paper of the first semester of the second year of college, aiming to test the actual performance effect of the English teaching strategies in this paper, and the English examination scores of the students in both classes were analyzed.

(3) Interview Method

At the end of the experiment, 20 students in the experimental class were randomly selected from the following grade bands (out of 100 points): 80-100 points (excellent), 60-80 points (qualified), and 60 points and below (unqualified) to be interviewed for additional clarification as to whether or not the English teaching strategy had improved the students' performance in college English. Under the guidance of the instructor, the student interview questions were determined according to the characteristics of the discipline and the actual situation. The student interview questions were as follows:

(a) How do you feel about the college English teaching strategy in this paper after using it for teaching?

(b) Do you think the college English teaching strategy in this paper has helped your college English performance? If so, in what ways?

(c) What is your opinion about the college English teaching strategy in this paper?

III. B. 3) Reliability test of the questionnaire

The questionnaire was based on a five-point Liker scale, in which students were asked to make basic choices based on their real situation by filling in 1, 2, 3, 4 or 5 in parentheses after each question, and the meanings of these numbers are as follows: 1=not at all, 2=usually not, 3=sometimes, 4=usually, and 5=completely. This study uses Cronbach's reliability coefficient and exploratory factor analysis for validity test in the test method, Cronbach's coefficient α takes the value range between 0-1, the higher the value of the coefficient indicates that the higher the reliability, the reliability coefficients of the various dimensions of the measurement scales used in this paper and the overall reliability coefficients are basically more than 0.85, therefore, it can be comprehensively stated that the questionnaire overall has a very good internal consistency, reliability Reliability. The overall KMO value of the questionnaire is 0.799, the KMO value ranges from 0-1, the higher the value of the coefficient, the better the validity. In this test the measured result is 0.799, which is greater than 0.6, indicating that the overall questionnaire is suitable for factor analysis and has good structural validity, and at the same time, according to the results of the Bartlett's spherical test, it can be seen that the chi-square=1942.434, $p<0.001$, which is significant at the 95% confidence level, so it also indicates that the data is very suitable for factor analysis and has good validity.

III. B. 4) Data collection

By counting the information, a total of 60 questionnaires were sent out to students, 30 in each of the two classes, and 60 valid responses were obtained, with a recovery efficiency of 100%. The findings provided by the questionnaires are true and are objective and generalized. This study also collected a large number of interviews, which are auxiliary information, by which teachers can have a more detailed understanding of the real learning situation of students and their own teaching effectiveness, after the interviews, the authors made a detailed record of the results of the interviews and organized and analyzed them in detail.

III. B. 5) Differential Analysis of Strategy Usage

(1) Definition of usage strategy levels

The magnitude of each strategy mean indicates the frequency of using the strategy, with mean scores of 0-1, 1-2, 2-3, 3-4, and 4-5 corresponding to always not using (low), usually not using (low), sometimes using (medium), usually using (high), and always using (high), respectively.

(2) Pre-intervention variability analysis

Through the questionnaire scale test, relevant research data were obtained to analyze the variability of strategy use between the experimental group and the control group before the intervention, and the results of the pre-intervention variability analysis are shown in Table 11, where CG and EG denote the control group and the experimental group, respectively. The results show that before the intervention, the strategy use grades of the control group and the experimental group are low and medium levels, and they do not have significant differences.

Table 11: Results of difference analysis before intervention

Item	Group	N	Mean	SD	T	P	Grade
1	CG	30	1.902	0.106	0.2873	0.8758	Lower
	EG	30	1.952	0.12			Lower
2	CG	30	1.966	0.131	0.1225	0.1623	Lower
	EG	30	2.032	0.157			Medium
3	CG	30	2.092	0.159	0.0183	0.6185	Medium
	EG	30	2.331	0.172			Medium
4	CG	30	2.405	0.192	-0.1351	0.4814	Medium
	EG	30	2.42	0.199			Medium
5	CG	30	2.427	0.258	0.2107	0.8331	Medium
	EG	30	2.547	0.264			Medium
6	CG	30	2.573	0.266	0.0193	0.7723	Medium
	EG	30	2.611	0.281			Medium
7	CG	30	2.629	0.331	0.0723	0.8963	Medium
	EG	30	2.688	0.332			Medium
8	CG	30	2.711	0.333	0.0814	0.5871	Medium
	EG	30	2.78	0.336			Medium
9	CG	30	2.853	0.362	0.0911	0.1743	Medium
	EG	30	2.892	0.371			Medium
10	CG	30	2.981	0.382	0.4136	0.2325	Medium
	EG	30	2.985	0.394			Medium

(3) Post-intervention variability analysis

Using the same method as above, the post-intervention difference analysis of strategy use between the experimental group and the control group was conducted, and the results of the post-intervention difference analysis are shown in Table 12. After a period of experimental intervention, it was found that the strategy use of the control group and the experimental group was medium and high, respectively, and satisfied the significant difference ($P<0.05$).

III. B. 6) Analysis of variability in English performance

Table 13 shows the comparison between the experimental group and the control group in the pre-test and post-test of English scores, according to the results of the pre-test, it can be seen that the scores ($t=0.123$, $p>0.05$), which indicates that there is no statistically significant difference between the experimental group and the control group. In the pre-test the difference between the experimental and control groups' English scores was not significant. In the post-test, the achievement ($t=2.181$, $p<0.05$), indicating that each factor reached significance at different significant levels and there is a statistically significant difference between the experimental and control groups. The post-test college English scores of the experimental group were significantly higher than those of the control group, and the average score of the experimental group was 88.08, which reached above the passing level. The control class was 63.81, slightly higher than the pre-test level but not greatly improved. The synthesis shows that the college English teaching strategy in this paper can improve students' English performance to a greater extent.

Table 12: Analysis of differences after intervention

Item	Group	N	Mean	SD	T	P	Grade
1	CG	30	2.019	0.2744	7.4041	0.0028	Medium
	EG	30	4.0005	0.2409			High
2	CG	30	2.1084	0.2247	6.4445	0.0041	Medium
	EG	30	4.021	0.295			High
3	CG	30	2.1352	0.2989	2.1881	0.0066	Medium
	EG	30	4.0613	0.2848			High
4	CG	30	2.5054	0.2373	6.3674	0.0079	Medium
	EG	30	4.0759	0.2028			High
5	CG	30	2.5436	0.2538	4.1981	0.0088	Medium
	EG	30	4.1791	0.2677			High
6	CG	30	2.6133	0.2492	4.9197	0.0086	Medium
	EG	30	4.2009	0.2312			High
7	CG	30	2.6904	0.2781	2.5813	0.0016	Medium
	EG	30	4.2611	0.2375			High
8	CG	30	2.8415	0.2322	6.1569	0.0027	Medium
	EG	30	4.3044	0.2095			High
9	CG	30	2.8669	0.293	3.3679	0.0032	Medium
	EG	30	4.3093	0.2864			High
10	CG	30	2.9977	0.2588	7.9119	0.0063	Medium
	EG	30	4.3348	0.2719			High

Table 13: Analysis of Differences in English Scores

Factor	Group	N	Mean	SD	T	P
Before	EG	30	62.33	3.298	0.123	0.481
	CG	30	61.29	3.128		
After	EG	30	88.08	3.277	2.181	0.024
	CG	30	63.81	3.411		

IV. Conclusion

The application of XGBoost algorithm for computational analysis of learning behavior can effectively improve the quality of college English teaching. The model evaluation indexes show that the accuracy rate of XGBoost algorithm reaches 0.9592, which is significantly higher than the control algorithm GBDT's 0.9209, KNN's 0.8383, SVM's 0.7335, DT's 0.7178, and RF's 0.6291. Teaching experiments validation shows that the teaching strategy formulated based on the computational analysis of learning behaviors significantly improves the students' English performance. The average posttest score of the experimental group was 88.08, which was 24.27 points higher than that of the control group. The three strategies of constructing an ecological classroom, implementing behavioral preventive measures, and creating an English teaching environment were able to enhance students' initiative and participation in learning. The results of the questionnaire survey showed that the average of the strategy use ratings of the students in the experimental group reached 4.0 or above, which was at the “high” level, while the control group remained at the “medium” level. The student interviews further confirmed that the personalized teaching method based on behavioral computational analysis can better meet the learning needs. University English teaching should make full use of computational analysis of learning behavior to accurately record and monitor learning data, provide personalized language input and output support, maximize learning efficiency, and improve teaching quality.

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