

Retraction

Retracted: English Teaching Achievement Prediction by Big Data Analysis under Deep Intervention

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] J. Guo, "English Teaching Achievement Prediction by Big Data Analysis under Deep Intervention," *Journal of Electrical and Computer Engineering*, vol. 2023, Article ID 9542465, 11 pages, 2023.

Research Article

English Teaching Achievement Prediction by Big Data Analysis under Deep Intervention

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Appropriate data analysis technology can make people use the online degree education, obtain the data and information generated in the learning management system, and provide a useful decision basis for optimizing the teaching and management process of online degree education. Data analysis technology can help English teachers better grasp students' learning situations and progress and optimize management. First, data analysis methods and decision tree algorithms are analyzed. Second, in data mining technology, the C4.5 decision tree method is used to construct an English score prediction model. Through the analysis of English learning-related information such as questionnaires and collected student test score data, the prediction of English teaching performance is analyzed from the perspective of teachers' in-depth intervention. The survey results are shown as follows: (1) The model is simulated and tested. The model's prediction accuracy is 98.20%, 99.10%, 99.40%, 98.70%, and 98.90%, higher than the standard accuracy of 97.5%. Additionally, the average response efficiency of the model is 99.42%, which can be used. (2) The failure rate of boys' final grades is 11%, and the failure rate of female students' final grades is 10%. There is only a 1% difference in the final grade failure rate between male and female students. The effect of gender on teaching performance is less pronounced. (3) As the number of practice questions increases, the rate of failing grades decreases. Thus, the data suggest that the number of practice questions affects instructional performance. (4) Teachers' intervention can improve students' English achievement. Increasing the intensity of the intervention also improves student achievement. Therefore, the follow-up research should increase the number of practice questions and teacher intervention in English teaching. The English teaching achievement prediction suggestion based on big data analysis is put forward, providing a reference for prediction management.

1. Introduction

Teaching intervention usually refers to the teaching operation mode in which teachers of various disciplines use the classroom teaching platform for their own courses and use psychological knowledge to help students "understand and change themselves [1]." Teaching intervention is conducive to students' self-adjustment in the learning process, improving the level of knowledge and skills and achieving better teaching effects [2]. In the fields of information technology and educational technology, data mining and statistical prediction models predict whether students can complete or pass courses based on variables such as effort level and grade point average [3]. Teachers provide students with effective feedback information through the acquired

data, guide students to use appropriate resources to complete teaching interventions, and improve the students' performance. The intensity of teacher intervention is used as a standard, which is divided into shallow and deep teaching interventions [4]. In-depth teaching intervention means that the teachers comment on the task works submitted by the students and give detailed suggestions [5].

In recent years, the concept of big data has gradually emerged. It is used to describe and define the massive data generated in the era of information explosion, as well as related technology development and innovation opportunities brought by big data [6]. Data mining is extracting information that people do not know in advance. Nonetheless, it is still useful for large amounts of incomplete, noisy, ambiguous, and random data [7]. It is a deep data

analysis method that mainly relies on artificial intelligence, machine learning, and statistical techniques to inductively reason data, dig out potential patterns, predict future trends, and provide support for decision-making [8]. Data mining and learning analytics technology are used to establish relevant systems to extract and standardize them and to provide a relevant decision-making basis for the optimal design of the network learning and management process [9]. Additionally, Zhu believed that the big data era of “data-driven schools, analysis, and education reform” has arrived. Data mining technology was born in the education industry. Based on data mining technology, he discussed English listening prediction strategies and training methods. This helps to train students to use predictive strategies and improve their listening comprehension. The listening data generated by the English skill training system were mined and analyzed. The data related to students’ listening are selected as features. Students’ listening test scores are simulated and trained to predict students’ listening. Evaluation and analysis show that data mining techniques can more accurately predict students’ listening [10]. Data mining algorithms mainly include the k-means algorithm, support vector machine (SVM) algorithm, decision tree model, and Bayesian model. The decision tree algorithm is a method of approximating the value of a discrete function. It is a typical classification method. First, the data are processed. Induction algorithms are used to generate readable rules and decision trees. Then, decisions are used to perform an analysis of the new data. A decision tree is a process of classifying data through a series of rules. Typical algorithms for decision trees are ID3, C4.5, classification and regression trees (CART), etc. The advantages of the decision tree algorithm are (1) high classification accuracy, (2) simple pattern generated, and (3) good robustness to noisy data. It is one of the most widely used inductive reasoning algorithms.

From the perspective of in-depth intervention, based on big data analysis technology, many learning data generated in the learning process of learners are collected and analyzed. The learning characteristics and problems of learners are to enable teachers to predict the students’ English achievement so as to judge the learning effect. Mixed data from brick-and-mortar classrooms and questionnaires are used as the basis. A DTA is used for classification. The prediction of English teaching achievement based on big data analysis is discussed under deep intervention.

2. Research Methods and Models

2.1. Deep Intervention Analysis. Intensive intervention is a teaching tool. Teacher interventions typically include all interventions that impact learning [11]. The data analysis results of the learning platform show that the teachers can improve learners’ intelligence levels and emotional cognition by adjusting the learners’ self-efficacy [12]. Teachers’ personalized interventions positively affect students’ academic performance and emotional cognition. According to the different intensities of teacher intervention, the concept of intervention is divided into shallow and deep teaching interventions [13]. The shallow intervention in classroom

teaching is mainly direct. In-depth intervention is mainly based on indirect intervention. In-depth teacher intervention means teachers implement clear, differentiated, and targeted interventions on learners. Typical deep intervention induction models are divided into primary, secondary, and tertiary interventions [14]. An analysis of the workflow of student behavior is shown in Figure 1.

In Figure 1, the four stages of behavioral analysis are as follows: (1) identifying the problem, defining the behavioral problem in observable terms, and making a reliable record of its frequency, intensity, and duration; (2) analyzing the problem, confirming the existence of the problem, identifying the student variables and educational variables that help to solve the problem, and formulating an appropriate plan; (3) implementing the plan, executing the plan, and providing corrective feedback to ensure that it is executed according to the predetermined plan; (4) conducting problem assessment to evaluate the effect of the intervention [15]. The flow of the student deep intervention model is shown in Figure 2.

In Figure 2, the deep intervention includes the following four steps: (1) identifying, describing, and analyzing the problem; (2) designing and implementing targeted interventions; (3) observing the progress of students and modifying the intervention measures according to the results of students’ response to the intervention; (4) planning and arranging the following measures in the process of problem-solving [16]. Since the deep intervention response model is implemented in the framework of multilevel intervention, these four steps need to be performed at each level of intervention [17].

2.2. Big Data Analysis Technology. The theoretical core of big data analysis technology is the data mining algorithm. Data mining is extracting implicitly unknown but potentially valuable information and knowledge from a large amount of incomplete, noisy, fuzzy, and random practical application data [18]. This kind of technology is an emerging discipline formed by the intersection and integration of multiple disciplines, integrating mature tools and technologies in many disciplines, including database technology, statistics, ML, pattern recognition, AI, and neural networks. [19]. Data mining techniques are classified from a theoretical point of view, as shown in Figure 3.

In Figure 3, data mining techniques can be theoretically divided into supervised and unsupervised algorithms. Among them, supervised algorithms mainly include logistic regression and decision trees. Unsupervised learning mainly includes clustering, nearest neighbor distance, and SVM [20]. The classification of data mining technology in terms of application is shown in Figure 4.

In Figure 4, data mining can be divided into classification, regression, cluster analysis, association rules, time series, and deviation-checking algorithms [21].

Data mining is mainly divided into four stages. Each stage has certain requirements. If a certain stage does not achieve the expected goal, it is necessary to stop the current process and go back to the previous step to adjust and

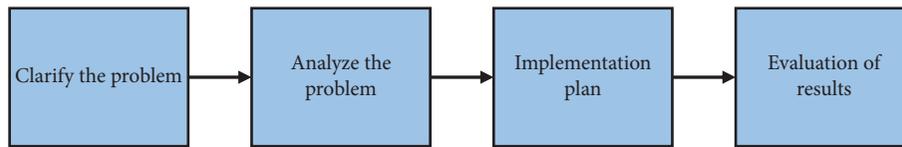


FIGURE 1: Flow of student behavior analysis.

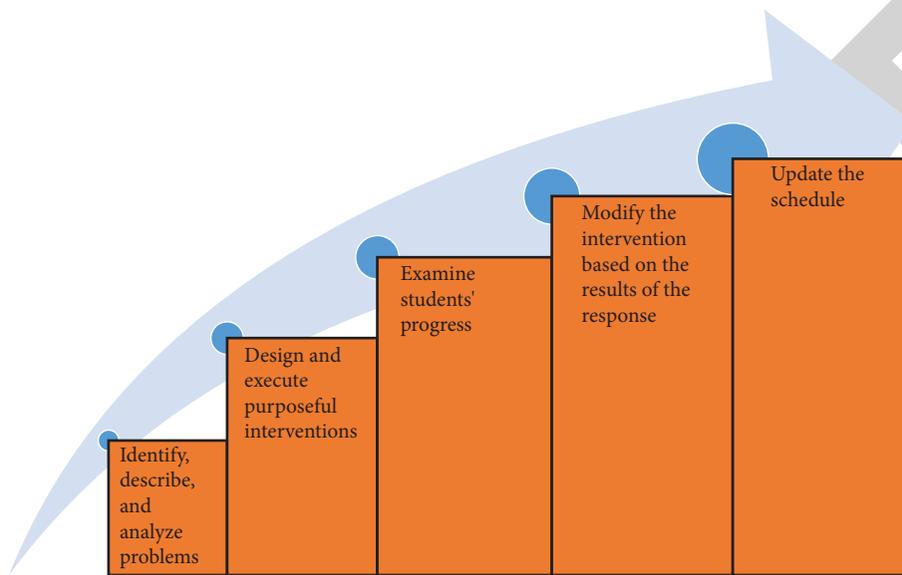


FIGURE 2: The flow of the deep intervention model.

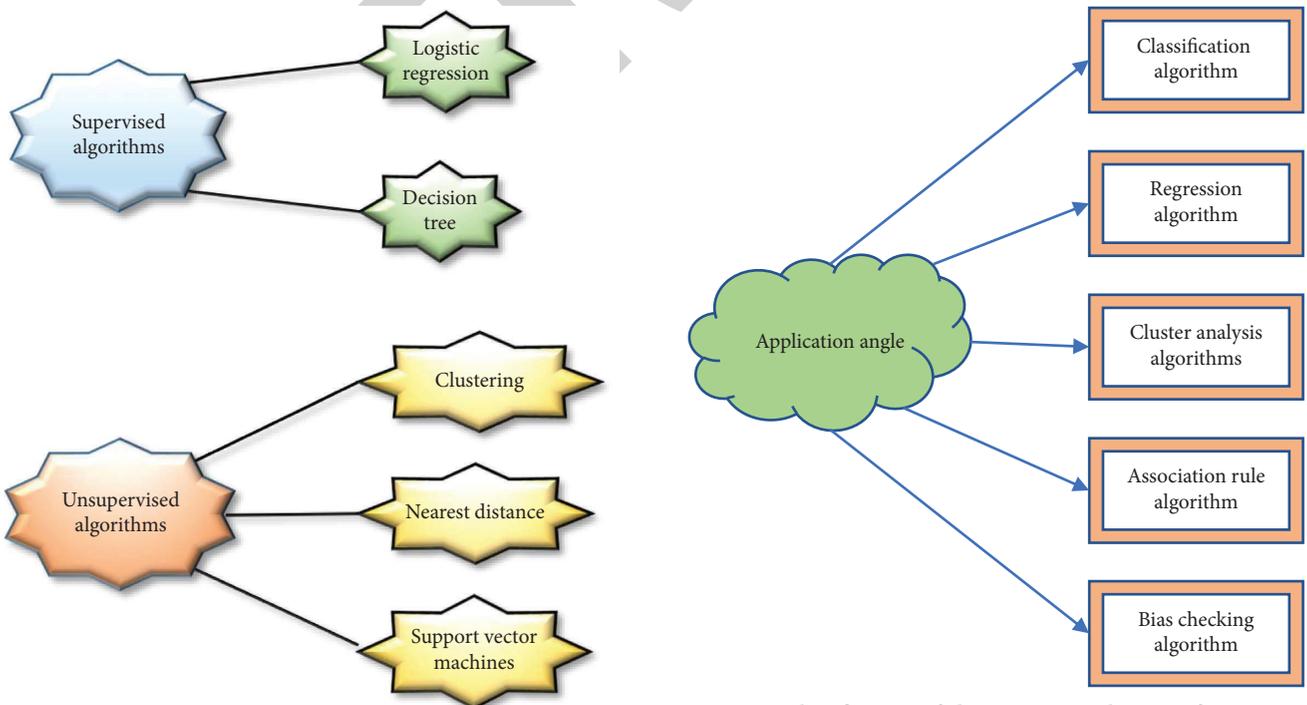


FIGURE 3: Classification of data mining techniques from a theoretical perspective.

FIGURE 4: Classification of data mining techniques from an application perspective.

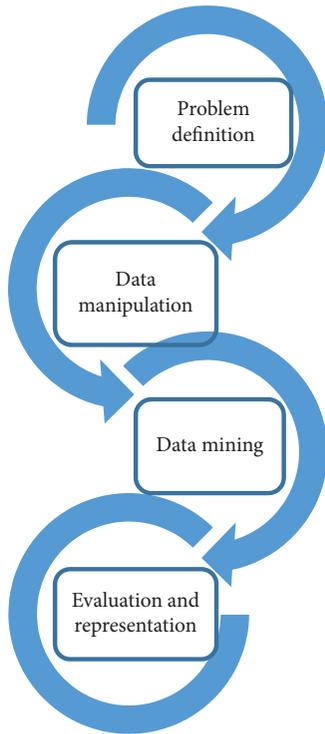


FIGURE 5: Stages of data mining techniques.

execute it again. Therefore, data mining is a process in which each step is interrelated and cyclical [22]. The four stages of data mining are shown in Figure 5.

In Figure 5, data mining can be divided into four stages: problem definition, data preparation, data mining, evaluation, and representation [23]. Usually, data mining technicians need to understand the background information of the data in advance and conduct in-depth communication with the demander. According to the target data type, the data mining algorithm is combined with the data mining task [24], and the mined dataset is preprocessed. This stage includes four further substeps. The steps of data preparation are shown in Figure 6.

In Figure 6, data preparation includes four steps: (1) Data selection: a mining task selects a dataset from a data source. (2) Data preprocessing: since the data to be analyzed are generally disorganized and contains noise, the target data are subjected to some simple processing. (3) Data conversion: the preprocessed data are formatted as needed, such as discretization and normalization. (4) Data loading: the processed data are loaded into a database, which has certain specifications to facilitate manipulation [25].

The data mining stage is to analyze the processed data. According to the mining tasks and objectives determined in the problem definition stage, an appropriate mining algorithm is selected for analysis [26]. The core technology of data mining technology is classification and clustering technology. The algorithms included in data classification and clustering techniques are shown in Figure 7.

In Figure 7, data mining algorithms can be divided into classification and clustering algorithms. In Figure 7(a), data

classification refers to analyzing a set of objects in a database to find their common attributes. Classification rules divide them into different preset categories. At present, classification methods include decision tree-based classification, such as Iterative Dichotomiser 3 (ID3) and C4.5 algorithm, statistical-based classification, such as Bayesian classification algorithm, and neural network-based classification, such as backpropagation algorithm. In Figure 7(b), the target of data clustering is related to the objects in the cluster, and the objects of different clusters are not related. The greater the similarity within a class, the greater the difference between classes and the better the data clustering effect.

2.3. Decision Tree Technical Analysis. The DTA is a commonly used classification algorithm in data mining. The node at the top level of the decision tree is the root node, which contains the collection of all data in the dataset. Each internal node represents a test on a feature, is a judgment condition, and contains a dataset that satisfies all conditions from the root node to the node in the dataset. The dataset corresponding to the internal node is divided into two or more child nodes. The number of branches is determined by the characteristics of the features on the internal nodes. In the decision tree construction process, choosing a split node is the most important. The important attributes are selected to judge the internal nodes analyzing the dataset with class tags. The process is iterated until a complete tree structure is generated or a specified threshold is reached to end the iteration. The structure of the decision tree is shown in Figure 8.

In Figure 8, the workflow of the decision tree is mainly divided into two steps. The first step establishes a basic training dataset by classifying and analyzing data. According to the training dataset, the regression algorithm is used to establish the corresponding decision tree. The second step tests the error of the decision tree step by step.

The decision tree selects the node with the highest information gain as the current split node during the construction process. A choice will minimize the amount of information required to divide the training samples in the resulting tree structure. If the training dataset S is divided according to the category attribute C , its classification information entropy is calculated as shown in the following equation:

$$H(S, C) = - \sum_{i=1}^m p_i \log_2(p_i), \quad (1)$$

where m is the total number of categories and p_i is the probability of that category i which appears in the entire training tuple. If the training dataset S is divided according to the conditional attribute A , then the classification information entropy of the conditional attribute A to divide S relative to C is shown in the following equation:

$$H(S, A|C) = - \sum_{j=1}^v \frac{|S_j|}{|S|} H(S_j, C), \quad (2)$$

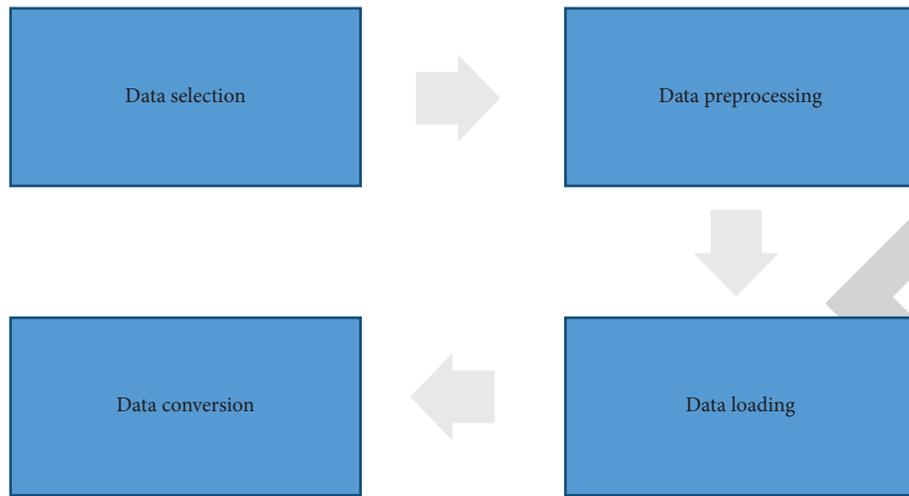
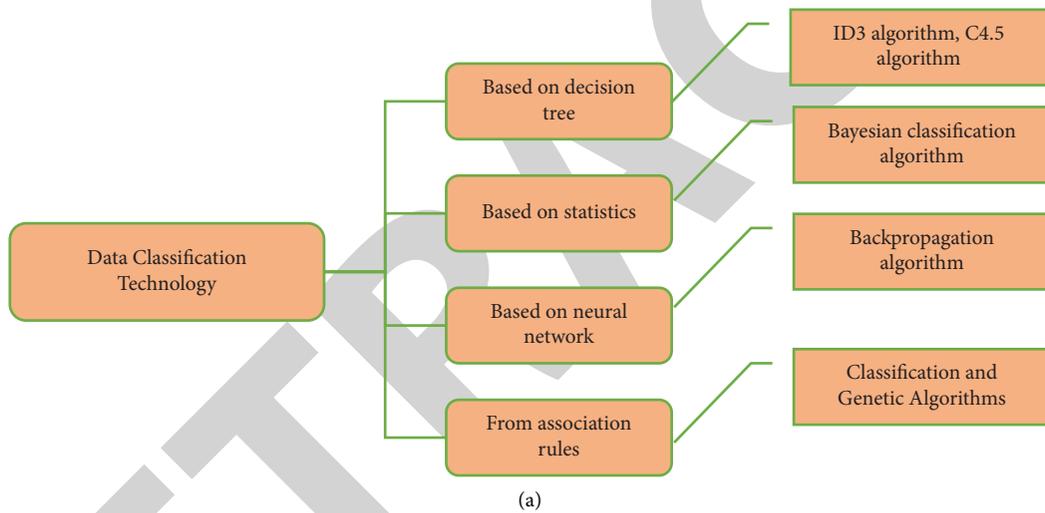
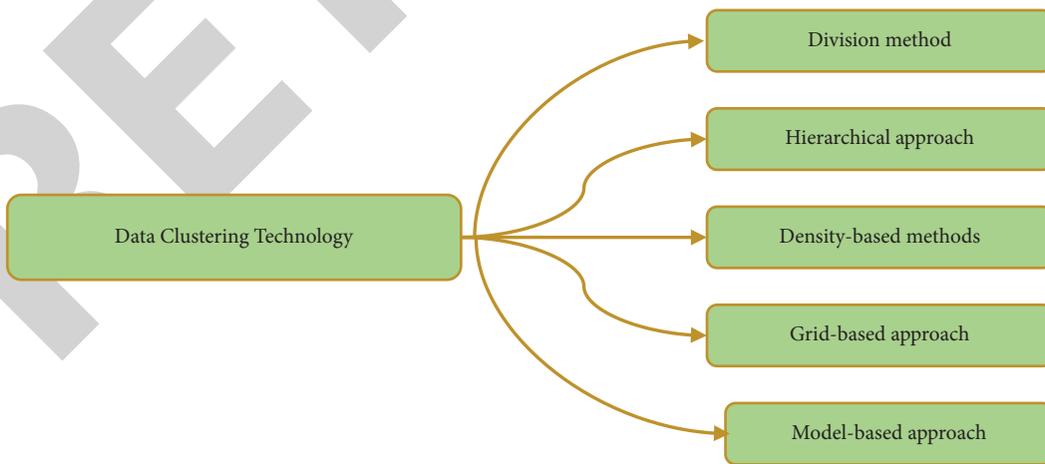


FIGURE 6: Steps of data preparation.



(a)



(b)

FIGURE 7: (a) Data classification algorithm and (b) data clustering algorithm.

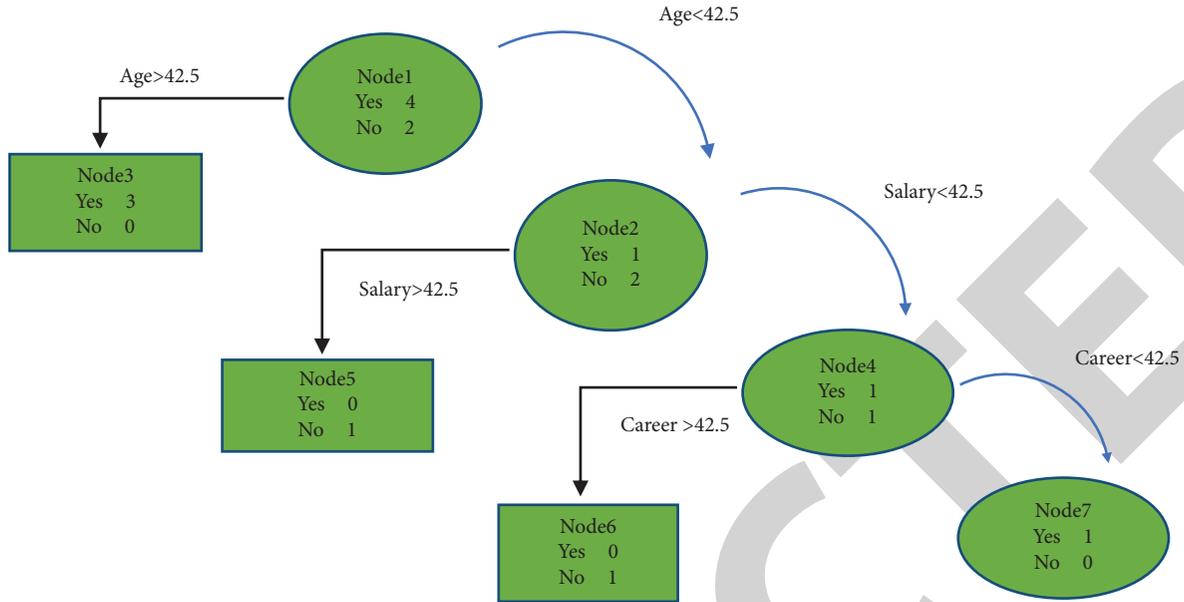


FIGURE 8: Structure of a decision tree.

where v is the number of values of conditional attribute A . The information gain of attribute A splitting dataset S is shown by the following equation:

$$\text{gain}(S, A|C) = H(S, C) - H(S, A|C). \quad (3)$$

In the C4.5 algorithm, the information gain rate of the attribute A splitting the dataset S is shown in the following equation:

$$\text{gain}_{\text{ratio}}(S, A|C) = \frac{\text{gain}(S, A|C)}{H(S, A)}. \quad (4)$$

In the classification tree, the Gini index of the probability distribution is expressed as

$$\text{Gini}(p) = \sum_{k=1}^K (1 - p_k) = 1 - \sum_{k=1}^K p_k^2, \quad (5)$$

where K is the number of categories and p_k is the probability that the sample point belongs to the K -th category.

In the two-class problem, if the probability that the sample point belongs to the first class is p , then the Gini index of the probability distribution is represented as

$$\text{Gini}(p) = 2p(1 - p). \quad (6)$$

For a given sample set D , its Gini index is

$$\text{Gini}(D) = 1 - \sum_{k=1}^K \left(\frac{|C_k|}{|D|} \right)^2, \quad (7)$$

where C_k is the sample subset of the k -th class in sample D and K is the number of sample classes.

If the sample set D is divided into two parts, D_1 and D_2 , according to whether the feature A takes a certain possible value a , then the Gini index at this time is represented as

$$\text{Gini}(D, A) = \frac{|D_1|}{|D|} \text{Gini}(D_1) + \frac{|D_2|}{|D|} \text{Gini}(D_2). \quad (8)$$

At this point, the Gini index represents the uncertainty of the set. The calculation for the decision tree gain error is shown in the following equation:

$$\alpha = \frac{R(t) - R(T_t)}{|N_{T_t}| - 1}, \quad (9)$$

where $R(T_t)$ represents the sum of the error costs of all leaves of a subtree T_t except the node t , $|N_{T_t}|$ is the number of leaf nodes in a subtree t , and $R(t)$ represents the error cost of a leafless node t , which is shown as

$$R(t) = r(t) * p(t), \quad (10)$$

where $r(t)$ is the error rate for node t and $p(t)$ represents the proportion of a subtree T_t to the total data.

Decision tree algorithms mainly include ID3, C4.5, and CART algorithms. As one of the most used algorithm models in data mining, the decision tree algorithm model can better classify English teaching models and lays a solid foundation for data analysis. Additionally, the information in English teaching is diverse, and the decision tree algorithm can simplify the processing through data pruning and other operations. Therefore, this work selects the decision tree algorithm as the basic algorithm for the operation of the model.

2.4. Prediction Model of English Teaching Results Based on Decision Tree Algorithm. This work designs an English teaching achievement prediction model based on the C4.5 in the decision tree algorithm. The C4.5 algorithm uses the information gain rate to select features to reduce the problem of large information gain caused by too many

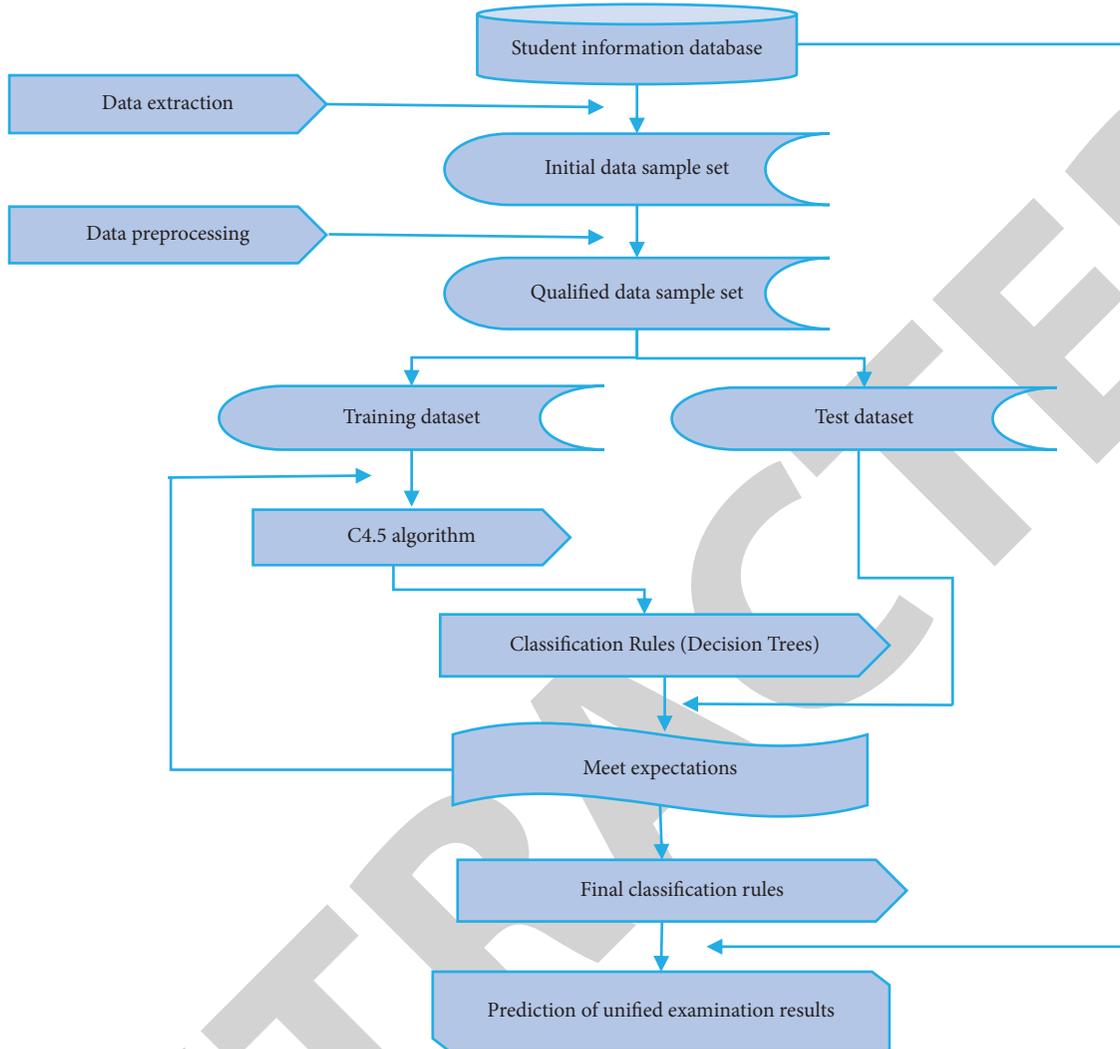


FIGURE 9: The prediction model of English teaching achievement based on decision tree algorithm.

eigenvalues. The algorithm has a better classification effect. The specific model is shown in Figure 9.

In Figure 9, first, certain sample information is extracted from the student information database to form an initial sample set. The initial sample set is subjected to pre-processing to remove the data attributes and contents irrelevant to the mining target to form a qualified dataset. Data mining provides clean, accurate, and more targeted data, which can reduce the processing load of algorithms and can improve the efficiency and accuracy of results. Eligible datasets are divided into training and testing datasets. The training dataset is input to the decision tree algorithm for training, and the output results are fitted to the test dataset. If the algorithm achieves the expected goal, it outputs the result; if not, it executes the training again.

2.5. Experimental Data Collection. The English scores of the students of various grades in a primary school in Anyang city are selected as sample data for research. The factors affecting English teaching performance are analyzed based on of the following factors: (1) Basic information about students, such

as name, gender, and grade, can be obtained through the student registration management system. (2) Information on students' test scores: the data table includes the student's student number, name, and test-related information. (3) Information on student performance in school: additionally, some sample values are randomly selected from the initial sample set as training samples to test the operation effect of the prediction model algorithm.

Through a random survey of the teaching performance of students in various grades in a primary school in Anyang, and the opinions of teachers and staff on students' performance, 100 questionnaires were distributed, and 94 valid questionnaires were recovered, with an effective recovery rate of 94%. The basic information of the investigators is shown in Figure 10.

In Figure 10, there are 45 males, 49 females, four teachers, 90 students, and 32 students from grade one to grade two, 30 students in grades three to four, and 28 students in grades five and six.

Statistical Product Service Solutions (SPSS) statistical software is used to analyze the data. Cronbach's alpha

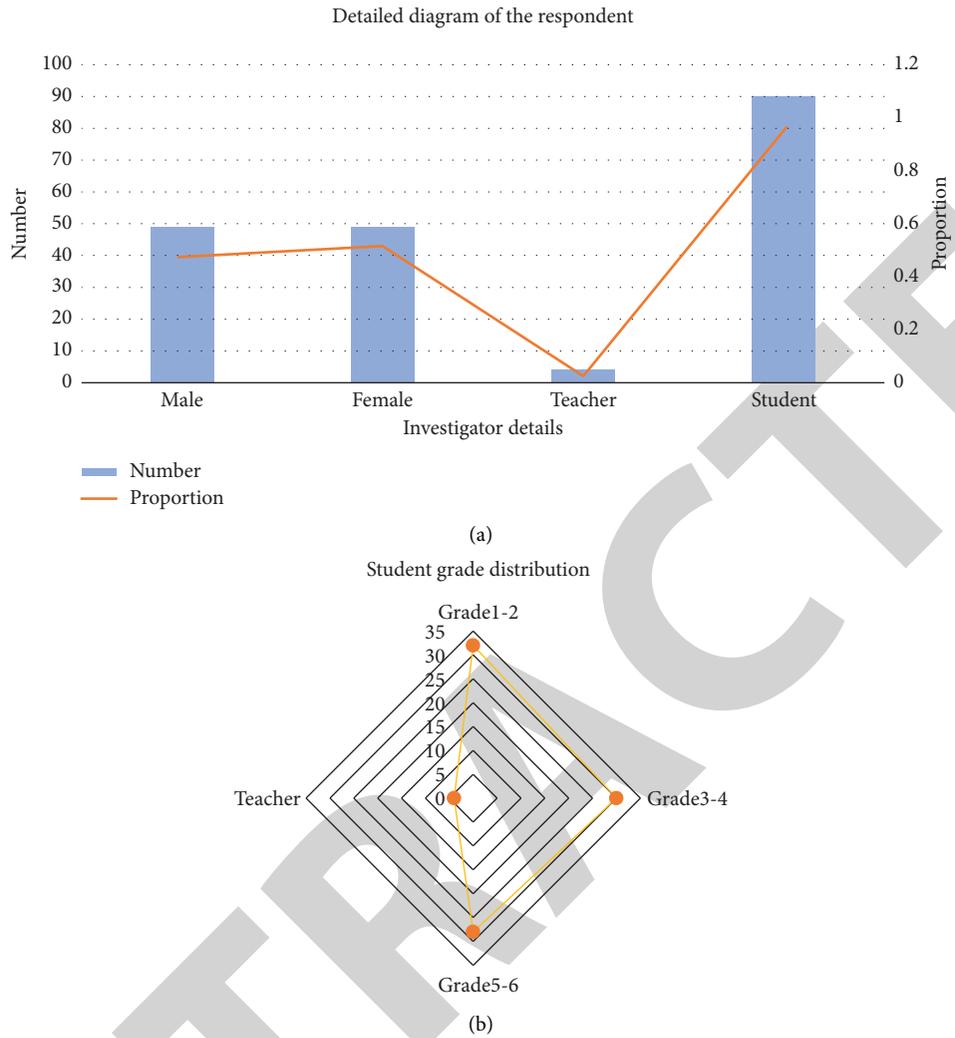


FIGURE 10: The details of the respondents: (a) the identity of the respondents and (b) the age distribution of the respondents.

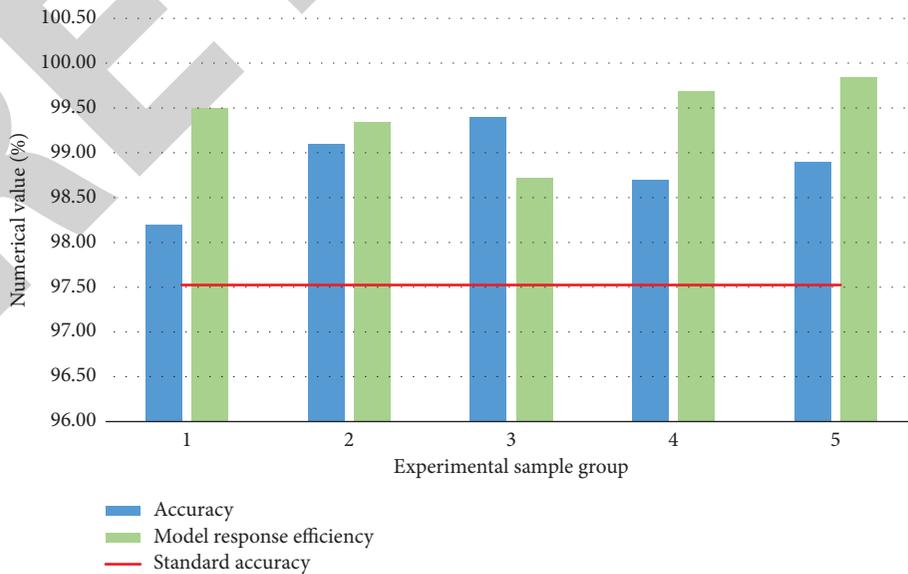


FIGURE 11: Results of the model running effect.

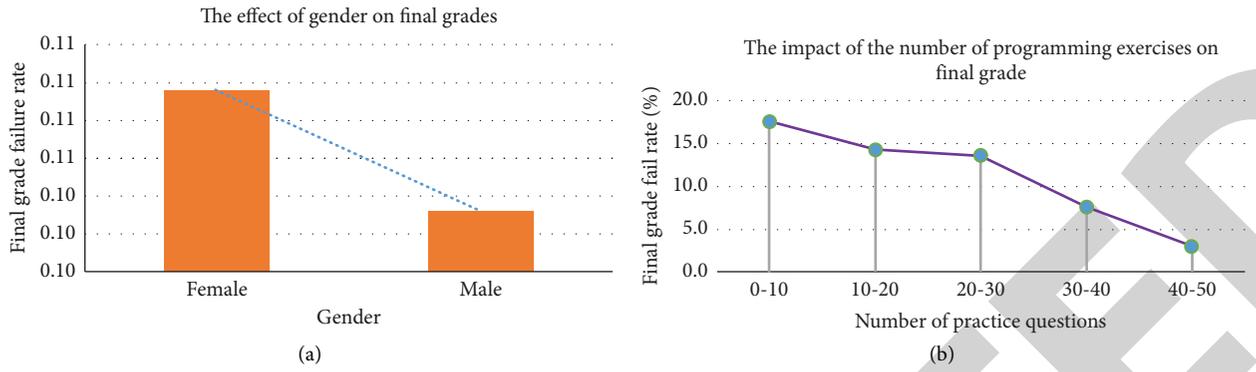


FIGURE 12: (a) Effect of gender on final grade and (b) effect of the number of practice questions on grade.

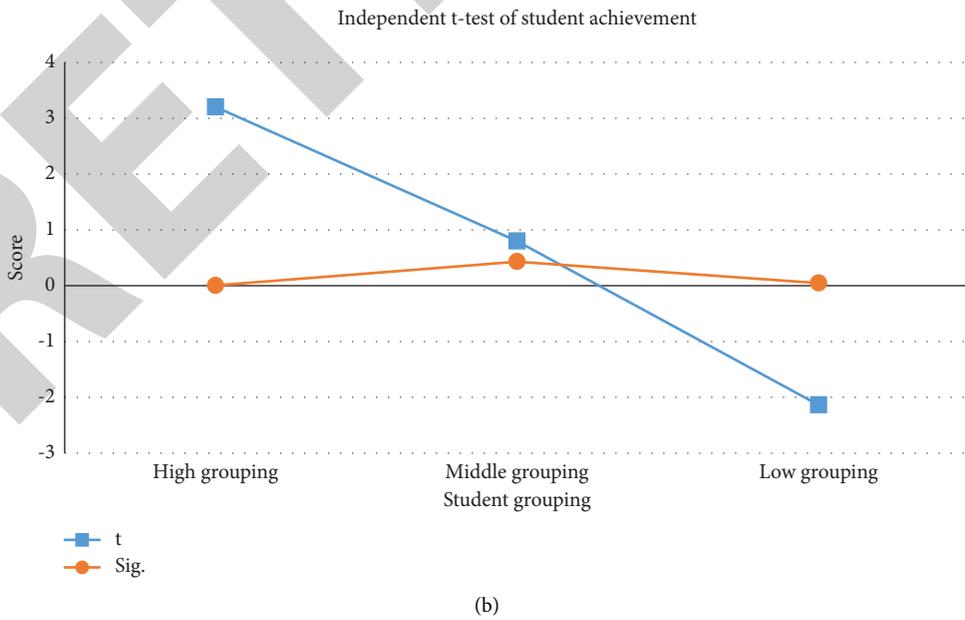
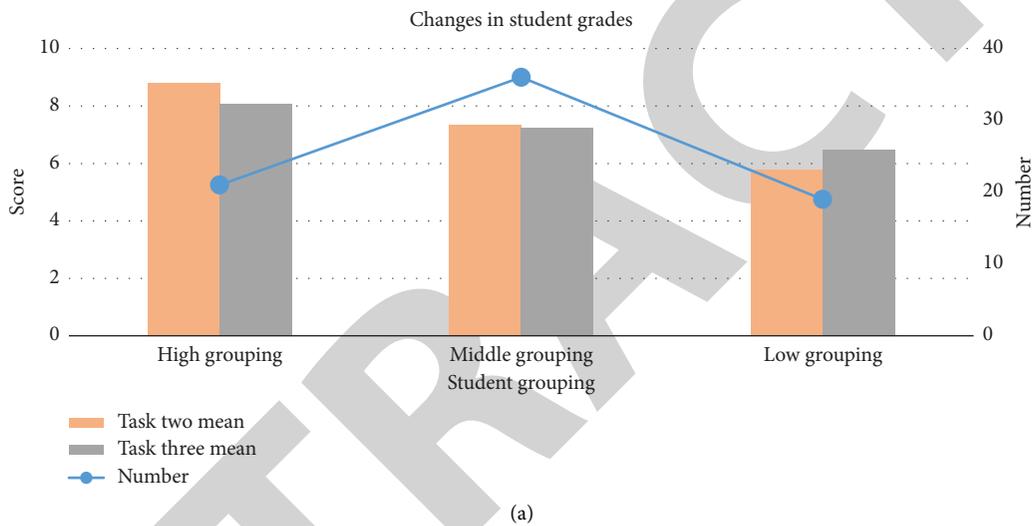


FIGURE 13: Graph of survey results: (a) changes in grades and (b) independent *t*-test analysis.

coefficient for the survey data is calculated and found to be 0.797. Within the scope of the reliability of the questionnaire, the results of the questionnaire are credible.

3. Results

3.1. Model Effect Analysis. Part of the dataset in the initial sample set is randomly selected as the test sample set. The prediction accuracy and processing time efficiency of the sample set are calculated, as shown in Figure 11.

In Figure 11, the running effects of the five sample groups set to test the model are used separately. The model's prediction accuracy is 98.20%, 99.10%, 99.40%, 98.70%, and 98.90%, which is higher than the standard accuracy of 97.5%. Additionally, the average response efficiency of the model is 99.42%, and the response efficiency is also in a high state. Therefore, the designed English teaching achievement prediction model based on the decision tree algorithm works well and can be used.

3.2. An Analysis of the Factors Affecting English Teaching Achievement. The effects of gender and the number of practice questions on grades are analyzed separately, as shown in Figure 12.

In Figure 12, there are 49 girls. Among them, the number of students who failed the final grade is 5, and there are 45 boys. The number of students who failed the final grade is 5. The ratio of the number of boys who failed in the final grade of the midterm to the total number of boys is the failure rate of the boys' final grade, which is 11%. The ratio of the number of female students who failed in the final grade of the midterm to the total number of female students is the ratio of female students' final grade failure, which is 10%. For this dataset, there is a 1% difference in final grade failure rates between boys and girls. Therefore, gender has a less obvious effect on teaching achievement. With the increase in the number of practice questions, the proportion of failing grades at the end of the term decreases successively, which are 17.49%, 14.29%, 13.46%, 7.59%, and 3.05%, respectively. As the number of coding questions practiced increases, the rate of failing final grades gets lower and lower. Therefore, the data suggest that the number of practice questions influences teaching performance.

3.3. Prediction of English Teaching Achievement Based on Big Data Analysis under Deep Intervention. The effect of a deep teaching intervention on teaching performance is further analyzed. After the course is launched, students' grades are predicted by setting three tasks. From the third prediction task, after each prediction, 76 students are selected for analysis and divided into high grouping, middle grouping, and low grouping, respectively. The students in the middle and low groupings are given teaching intervention, while those in the high grouping are not given teaching intervention. After obtaining the actual grades of all students for task 3, the mean scores for tasks 2 and 3 are calculated. Paired samples *t*-tests are

used to obtain instructional intervention results in SPSS software. Among them, *t* is the significance test statistic, and the probability Sig. of the corresponding significance test statistic is obtained according to *t*, as shown in Figure 13.

In Figure 13, (1) in high grouping with no intervention, tasks 3 and 2 show a significant decrease trend; (2) in middle grouping, the average score of the experimental group students in tasks 3 and 2 shows a trend of improvement. The scores of the students in the control group showed a significant decreasing trend, and the overall trend is decreasing; (3) in low grouping, there is a significant trend of improvement compared with the average scores of students in task 3 and task 2. The scores of the students in the control group also improved, but not significantly, showing an overall trend of improvement. These data show that teaching intervention improves the student performance, and the greater the investment in teaching intervention, the better the effect.

4. Conclusion

Based on the decision tree algorithm, a prediction model for English teaching outcome is proposed. Under intensive intervention, the model is studied. The survey results show that the model prediction accuracy is 97.5% higher than the standard. Additionally, the average response efficiency of the model is 99.42%, the failure rate of male students is 11%, and the failure rate of female students is 10%. Therefore, the effect of gender on teaching performance is less obvious. As the number of practice questions increases, the failure rate gradually decreases. Thus, the data suggest that the number of practice questions affects instructional performance. The number of practice questions has a significant impact on English teaching performance. Teachers' intervention can improve students' English performance, and intervention intensity will also improve students' performance. Therefore, follow-up research should increase the number of practice questions and teacher intervention in English teaching. Due to the short time and limited sample size, there are certain deficiencies in the scope and depth of teaching intervention. In the future, this article will expand the scope of teaching interventions and will take deeper teaching interventions. In addition, big data analysis technology keeps pace with the times and will update and utilize new technologies in the follow-up, deeply integrate theory and practice, and design an English teaching achievement prediction model with more teaching theory characteristics. The innovation lies in using computer and data mining technology to analyze the traditional teaching results, making the results more credible. Additionally, teacher intervention factors are introduced to ensure the integrity of teaching performance predictors.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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