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Effectiveness Evaluation of Online Interactive Mode for College English: A Perspective Based on Big Data Analysis

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ABSTRACT

Online interactive teaching mode is one of the important ways for modern universities to achieve effective teaching. To enhance the reliability of the effectiveness evaluation of online interactive teaching mode, this paper constructs a college English online interactive mode effectiveness evaluation model based on big data mining algorithms. The model achieves effective data preprocessing and results inthe ranking of evaluation data based on the teaching effectiveness evaluation system. The experimental results show that the proposed English online interactive mode effectiveness evaluation model has lower evaluation result error, better reliability, authenticity, and flexibility, and better fits the actual evaluation results of the English online interactive mode.

Keywords: Big Data, College English, Online Interactive, Effectiveness Evaluation

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1. Introduction

The application of big data technology in the field of education not only promotes the development of educational informatization but also changes the teaching mode of teachers and the learning methods of students. The two's deep integration significantly impacts the educational environment, subject relationships, learning paths, and effectiveness evaluation of teaching modes. In recent years, online teaching has become an important way for contemporary college students to learn, and it is also one of the important teaching methods for universities in the future. It breaks the constraints of traditional teaching, realizing the purpose of "learning anytime, anywhere." Online teaching mode differs significantly from traditional teaching mode. It changes the core position of teachers in teaching and gives students more opportunities for active learning. With the development of online teaching, the demands and requirements of teachers and students for online teaching modes are continuously increasing. Various online teaching modes have emerged, providing new teaching methods for online education and

accelerating the process of educational reform. Although online education guarantees teaching effectiveness to some extent through novel teaching methods and information technology, many problems have gradually emerged in practice, among which the evaluation of online teaching effectiveness has become a hot topic of concern.

Teaching effectiveness evaluation is an important part of educational work, and it plays a vital role in clarifying the direction of educational reform. A scientifically perfect teaching effectiveness evaluation method can make valuable judgments on teaching conditions and results from multiple levels and dimensions, providing effective, objective, and scientific feedback information for teaching development and reform. The effectiveness evaluation based on traditional teaching modes is mainly achieved through expert evaluation and student assessment, which relies heavily on human efforts and incurs high time costs. It lacks objectivity and accuracy, and it lacks accuracy and applicability in online teaching evaluation. At the same time, a single evaluation method makes it difficult to provide a large amount of feedback information that meets the requirements and demands of online teaching modes and cannot provide real-time feedback information for online teaching modes. Different online learning platforms collect and process relevant evaluation data based on their corpora, preferences, and other factors to better evaluate the effectiveness of online teaching. However, due to the limitations of evaluation methods, it isn't easy to achieve effective, personalized, and humanized evaluation of English learning in different university online English learning scenarios. Different evaluation methods also lead to certain differences in the evaluation results obtained.

Based on this, this paper combines the feedforward neural network model and big data technology to construct a college English online interactive mode effectiveness evaluation model. It achieves data processing of evaluation data for online interactive teaching mode. It improves the accuracy and flexibility of effectiveness evaluation through data mining algorithms and constructing an evaluation index system. It more intuitively shows the evaluation results and provides more effective and reliable feedback information for English online interactive teaching mode.

2. Online Teaching Interactive Mode Effectiveness Evaluation

The theory of teaching evaluation originated from the Simon intelligence test in France in the 19th century. In the 20th century, the United States proposed that teaching evaluation is the result of performance and the process of evaluation, emphasizing the process and result of teaching evaluation. Based on this, the theory of teaching evaluation gradually developed from the single evaluation result to the "process + result" teaching evaluation content nowadays. Currently, teaching effectiveness evaluation includes the evaluation of the completion of teaching objectives by teachers, the effectiveness of students' learning after class, the overall evaluation of teachers' teaching, and students' self-evaluation. In addition, scholars have added expert evaluation to teaching effectiveness evaluation to increase the reliability of teaching evaluation. However, influenced by various objective factors, test results are still the main influencing factor in evaluating traditional classroom teaching effectiveness. Some scholars pointed out that attaching too much importance or relying too much on test results as the result of teaching effectiveness evaluation not only inhibits students' enthusiasm for learning but also conceals problems in teachers' teaching. The evaluation results lack objectivity and dynamism.

To improve teaching efficiency and effectiveness, information technology has been widely used in education, and online classrooms have gradually become an important way for modern students to learn in the classroom. Compared with traditional teaching, online classrooms have subverted the position of teachers and students in teaching, giving students more autonomy and flexibility. At the same time, teachers have diversified their teaching

methods and enriched their teaching content through online platforms. With the development of online teaching modes, some scholars pointed out that the practicality of traditional teaching effectiveness evaluation methods in online teaching effectiveness evaluation is relatively low and lacks objectivity and accuracy. Based on this, some scholars proposed a process evaluation method, which achieves dynamic observation and evaluation of students' overall learning process through the backend data of the platform. It completes the overall evaluation based on factors such as students' learning status, attitude, and performance and makes targeted adjustments to teaching methods. Some scholars have also built a classroom teaching effect evaluation system based on big data and cloud computing technology, including modules such as classroom attendance, online testing, peer evaluation, and teacher evaluation. However, this evaluation system cannot effectively evaluate subjective issues and is prone to making one-size-fits-all evaluations of different students' learning levels and differences. In addition, some scholars pointed out that whether online or offline, self-evaluation and peer evaluation will be greatly affected by emotions, attitudes, and other factors, making it relatively difficult to carry out. Some scholars also pointed out that the evaluation of online teaching effectiveness should be based on quantitative indicators for qualitative evaluation. However, many comprehensive evaluations based on big data technology still lack quantification in qualitative evaluation and have not fully played a role in evaluation.

3. Online Interactive Mode Effectiveness Evaluation Model

3.1 Feedforward Neural Network and Big Data Technology

The online interactive teaching mode can change how college students acquire knowledge, enhance students' enthusiasm for active learning, and strengthen the targeted deep learning of English. Through an interactive online mode, timely communication can be achieved between teachers and students, as well as among students, improving communication efficiency and enhancing the timeliness of English teaching. Therefore, there is a certain correlation and continuity between the English teaching text data and the corresponding evaluation data, and each word in the text data has a decisive impact on the adjacent words in the previous and following texts. The evaluation model that combines feedforward neural networks and big data technology can effectively segment data based on feature values and the correlation between nodes.

The effectiveness evaluation model is divided into input, output, and mapping. At the input level, the input data refers to the specified words in the evaluation text and their corresponding vectors in the context. These text data need to be segmented based on their characteristics before being input into the model. Text data can include discrete data and continuous data. The segmentation of discrete data not only needs to preserve various feature values but also ensure the correspondingness of each node. The segmentation of continuous data requires adherence to certain order rules so that each interval of decomposition can have corresponding attributes and nodes. Since different types of evaluation text data are generated uncertainly, this paper will use information entropy to describe the sum of their time uncertainties; that is, there is a positive correlation between uncertainty and entropy. Formula (1) shows the expression of information entropy

$$Ent(M,J) = -\sum_{i=1}^{n} \frac{M_i}{i} \log_2 \frac{M_i}{i} \tag{1}$$

The analysis dataset with attributes is represented as M, and its corresponding attribute description is J. The corresponding information entropy is denoted as i. The description of the example set before the splitting of the attribute analysis dataset is denoted as Mi, where Mv is the quantity, and $n$is the amount of attribute splitting.

After the statistics of each attribute analysis dataset, the corresponding information gain value can be obtained as shown in equation (2):

$$Gain(M,J) = Ent(m) - \sum_{v=1}^{v} \frac{Mv}{v} Ent(Mv) \quad (2)$$

In equation (2), the description of information gain value is (*M, J*), the result obtained based on the entire attribute set is represented as *M*, and the result obtained based on the attribute value set is represented as *Mv*, where *v*is the quantity of attribute values.

3.2 Evaluation Data Preprocessing and Evaluation Index System

The evaluation data of the English online interactive teaching mode lacks uniformity and completeness, and the probability of noise problems during data processing is relatively high. Therefore, this paper preprocesses the evaluation data using big data mining algorithms. Invalid texts must be filtered before redundant data is removed during processing. At the same time, texts that do not contain Chinese or English words need to be screened, and irrelevant texts need to be filtered based on reading file annotations to judge the evaluation data. Big data mining algorithms are used to process indicators based on the Spearman correlation coefficient, as shown in formula (3) for the calculation of indicator correlation:

$$Cov(x,y) = E(xy) - E(x)E(y) \quad (3)$$

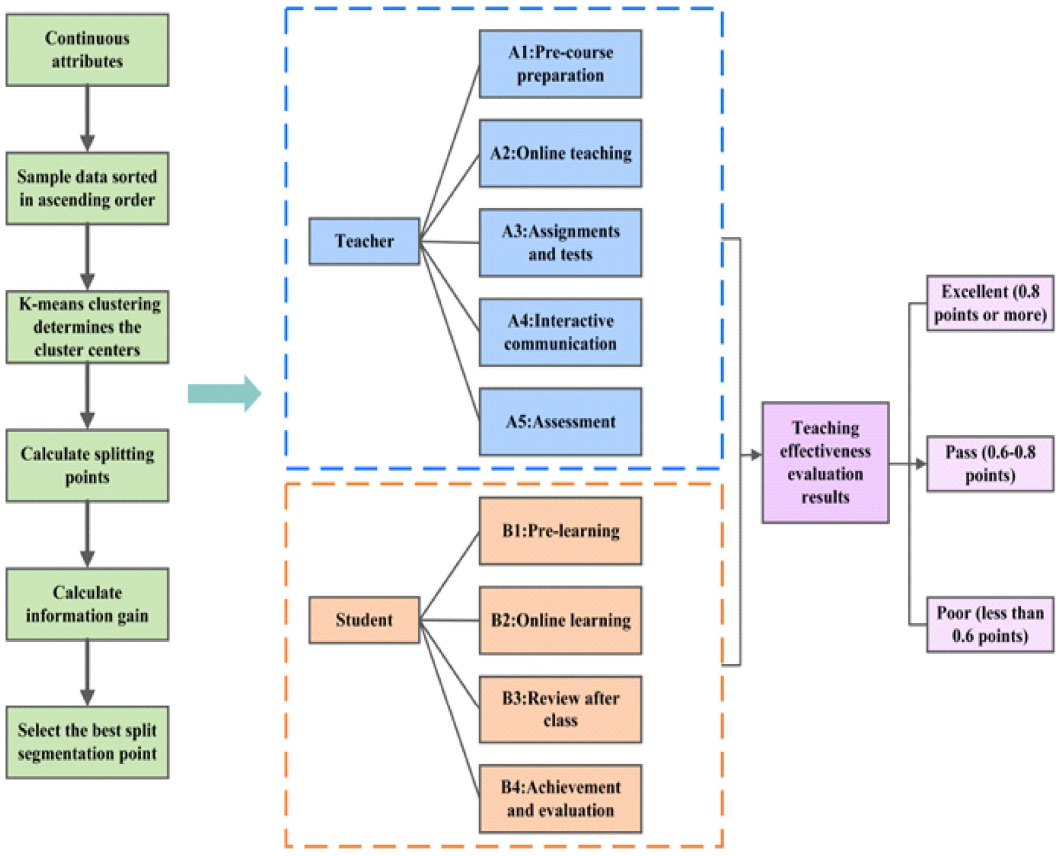

Figure 1. Process and Results of Evaluation Indicator Selection for English Online Interactive Teaching Mode

In this context, the coefficient is represented as *Cov*, and there is a correlation between the two. The correlation coefficient is denoted as xy, and the Pearson coefficient is described as $(x),(y)$. Based on the values and associations in the correlation table, the selection of indicators is conducted. Let the selected indicators be represented as, and the mean values of their correlation coefficients with other indicators be represented as. When an indicator is retained, it is retained; otherwise, it is retained. All indicators are compared pairwise following the above procedure.

The construction of the evaluation index system for English online interactive teaching mode is based on its application requirements and expected effectiveness goals. The selection process and the evaluation indicators results of the evaluation indicators are shown in Figure 1. The indicator selection method is based on the K-means algorithm, which completes data sorting based on the continuity of evaluation data. Then, the K-means algorithm is used to obtain data cluster centres, calculate segmentation points and information gain data, and finally, the best nodes are selected to complete data segmentation.

The indicator system mainly includes two modules: teacher and student. The teacher's primary evaluation indicators are pre-class preparation, online teaching, assignments and tests, interactive communication, and assessment. The student's primary evaluation indicators include pre-class preview, online learning, post-class review, grades, and evaluation. Each primary indicator also contains corresponding secondary indicators. Based on multiple indicator results, the effectiveness of the English online interactive teaching mode is divided into evaluation levels and presented intuitively.

4. Experimental Results of the University English Online Interactive Teaching Mode Effectiveness Evaluation Model

To validate the effectiveness of the university English online interactive teaching mode evaluation model based on big data mining algorithms, this study selected two other teaching effectiveness evaluation methods for comparative experiments. One method is based on the KANO model, and the other is based on the teaching process. The experimental subjects were students from a certain class in the second year of a university. During the experiment, the effectiveness of the English online interactive teaching mode in this class was evaluated using the three evaluation methods. Considering the differences in the output results of the three evaluation methods, a normalization process was conducted using formula (4).

$$W = \sum_{i=1}^{n} p_i \times \alpha \times 0.1 \tag{4}$$

The normalized evaluation results are represented as, and the output results of any evaluation method are represented as. The conversion coefficient between the three methods is represented as W, and the number of evaluation methods is n. The normalized evaluation results have a value range of, and values closer to 0 indicate lower effectiveness of the online interactive teaching mode.

Figure 2 shows a comparison of the evaluation results of the three university English online interactive teaching mode effectiveness evaluation methods. The blue data represents the teacher evaluation module, the orange data represents the student evaluation module, and the red line represents the actual evaluation results. The data in the graph shows that, for both the teacher and student evaluation modules, the evaluation results of the English online interactive teaching mode in this study have the lowest error compared to the actual evaluation

results, and there is consistency between the evaluation levels and actual evaluation levels. In contrast, the other two effectiveness evaluation models have relatively small errors between some indicators and actual evaluation results. Still, the accuracy of other indicator results is lower, and there are inconsistencies in the evaluation levels. Furthermore, this study's teaching effectiveness evaluation model can provide effective evaluations based on different indicator requirements, showing better evaluation flexibility compared to the other two evaluation models and generating more personalized and humanized evaluation results. Therefore, this study's English online interactive teaching mode effectiveness evaluation model exhibits better evaluation accuracy, yielding results closer to the actual situation and effectively reflecting the true effectiveness of the English online interactive teaching mode when applied.

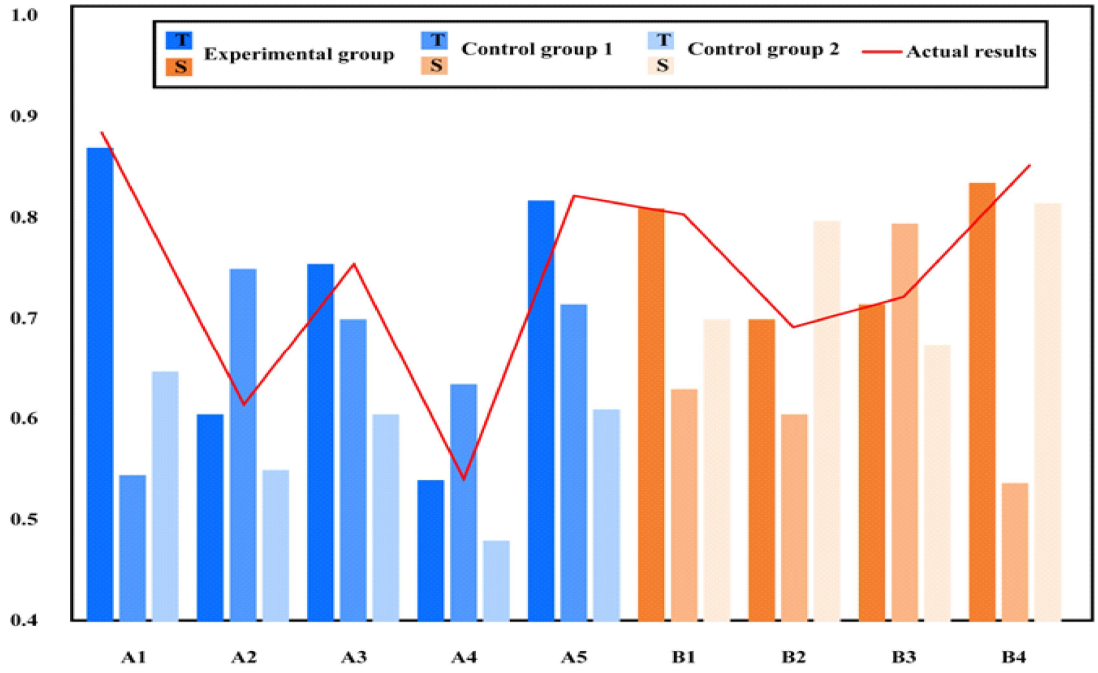

Figure 2. Comparison of Evaluation Results for Three University English Online Interactive Teaching Mode Effectiveness

Based on the results shown in Figure 2, it can be observed that in the teacher evaluation module, the evaluation result for the interactive communication indicator is the lowest. In contrast, the online learning and post-class review indicators in the student evaluation module have relatively low scores. Combining the results of the big data mining, it can be found that the choice of different teaching methods by teachers in the English online interactive teaching mode has an impact on the interaction between teachers and students and the effectiveness of online teaching. As shown in Figure 3, the statistical results of the selection of teaching methods by English teachers in online teaching at this university are presented. From the results in the graph, it can be seen that English teachers generally choose multiple interactive teaching methods, with live broadcasting and recorded lectures being the most commonly selected. Additionally, teachers increase interaction with students by creating active classrooms, and only a small number of teachers, due to lack of experience, have low interactivity in online English teaching. Therefore, the evaluation results for English online teaching with full live broadcasting and active interaction with students are higher compared to less interactive online classrooms. Moreover, good interaction enhances students' online learning effectiveness and increases their proactivity in post-class reviews.

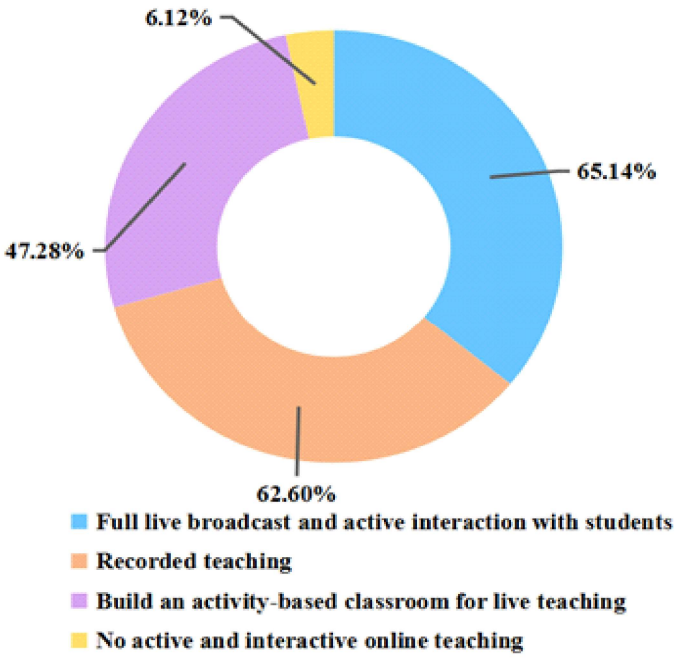

Figure 3. Statistical Results of English Teachers' Selection of Teaching Methods in Online Teaching

In summary, the university English online interactive teaching mode effectiveness evaluation model based on a big data mining algorithm has higher accuracy in evaluation results compared to the other two teaching effectiveness models, and it can better reflect the effectiveness of the English online interactive teaching mode in practical applications. Furthermore, combining the results of big data mining reveals the factors that influence the indicators of the English online interactive teaching mode, providing timely and intuitive feedback on the evaluation results and existing issues, thus offering effective, objective, and accurate feedback for improving the teaching mode.

5. Conclusion

The online interactive teaching mode is one of the important approaches for contemporary university students to learn English. It breaks the constraints of traditional English teaching, broadens the space for English learning among university students, and enhances the interaction and communication between teachers and students. However, the previous teaching effectiveness evaluation methods relied on subjective manual evaluation or implemented a one-size-fits-all evaluation on online platforms, lacking flexibility and accuracy. Therefore, this paper constructed a university English online interactive teaching mode effectiveness evaluation model from the perspective of big data analysis and incorporated feedforward neural networks to improve the segmentation accuracy and correlation of evaluation data. Additionally, the K-means algorithm was employed to effectively select evaluation indicators, enhancing the flexibility and intuitiveness of the evaluation model. The experimental results show that the evaluation model presented in this paper outperforms the other two comparative teaching effectiveness evaluation models in accuracy and can better reflect the teaching effectiveness. Moreover, by combining the results of big data mining, existing issues in the English online teaching mode can be identified, resulting in more intuitive, effective, objective, and flexible evaluation results.

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