Research Article

Application of Fuzzy K-Means Clustering Algorithm in the Innovation of English Teaching Evaluation Method

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As an important course in colleges, the teaching quality of English courses directly affects the efficiency of talent training. Carrying out English teaching evaluation is conducive to solve the problems existing in English teaching timely, improve the teaching level, and promote the demand of English curriculum teaching reform. However, the traditional English teaching evaluation methods adopted by colleges have some disadvantages, such as inaccurate evaluation results and long evaluation time, which urgently needs to innovate and reform the English teaching evaluation method. With the wide application of modern information technology in English teaching, the fuzzy K-means clustering algorithm can be used to construct a new English teaching evaluation model, which can effectively make up for the shortcomings of traditional teaching evaluation methods. This study proposes an English teaching evaluation method based on the fuzzy K-means clustering algorithm. This study uses the association rule analysis method under the data mining technology to preprocess the English teaching data, establishes the hierarchical structure model combined with the applying steps of the analytic hierarchy, and constructs the judgment matrix, carries out the hierarchical ranking and consistency test, and defines the specific weight of each index in the teaching evaluation index system, transforms the problem of English teaching evaluation into solving the K-means clustering objective function, realizes the scientific and accurate evaluation of English teaching, and provides a guarantee for improving the quality of English teaching. The results show that the English teaching evaluation method based on the fuzzy K-means clustering algorithm has a good evaluation accuracy, ensuring that the evaluation error is less than 6%, and the evaluation time is only 3.9 seconds, which significantly reduces the evaluation time.

1. Introduction

As an important part of English teaching, English teaching evaluation can reflect the teaching results in time, optimize the teaching plan, and improve the professional ability of teachers [1, 2]. Whether the effectiveness of English teaching can be maximized, whether the evaluation work is scientific, and whether the evaluation conclusion is effective depend on whether the evaluation index system is designed reasonably [3, 4]. However, as a systematic project, this system inevitably has many problems. For example, the index system reflects too much identity. That is, there is a situation that one index system covers all problems in the evaluation system, ignoring the diversity and multi-level problems, resulting in unfair and incomplete evaluation results [5–7].

Reference [8] uses grey correlation analysis method, constructs the multimedia teaching quality classifier based on neural network, and innovates the teaching quality evaluation method, to clarify the index weight in teaching evaluation system. However, Reference [9] sets up learning samples and carries out sample training under the technology of BP neural network and data mining, so as to create a new teaching quality evaluation model and implement teaching evaluation more efficiently in universities. The entropy-weight evaluation method is adopted in Reference [10] to clarify the initial evaluation results and index weights, in order to ensure the impartiality of the evaluation results, and constructed teaching evaluation system. In addition, the advantages of the adaptive adjustment operation of the individual adaptive mutation genetic algorithm are
utilized to create a perfect teaching quality evaluation model. While the teaching mode is gradually diversified, the new teaching mode including network teaching has been popularized and applied, which makes the teaching data increase day by day. This puts forward higher requirements for teaching evaluation. However, there are great limitations in the above teaching evaluation methods, which cannot process massive teaching data and leads to the poor effect of teaching evaluation. Thus, new teaching evaluation methods should be explored and studied to optimize the effect of teaching evaluation constantly.

The fuzzy K-means clustering algorithm can organize and divide a large amount of teaching data, form many mutually exclusive clusters, stipulate that each object just or must belong to each cluster, and evaluate the quality of divided clusters based on the objective function, so as to carry out adjustment processing. The algorithm avoids the interference of noise data and improves the accuracy of clustering. In the following research on innovative evaluation methods of College English teaching, the fuzzy K-means clustering algorithm is used to realize the transformation of evaluation mode, and brand-new teaching evaluation approaches are used to implement relevant evaluation work, which realize continuous optimization of English teaching.

2. English Teaching Data Preprocessing

When applying the new English teaching evaluation method based on the fuzzy K-means clustering algorithm, the first step is to carry out the preprocessing of English teaching data, which lays a foundation for the later evaluation work.

2.1. Data Mining for English Teaching. The existing English teaching data processing methods can not meet the growing demand for rich supply of information processing. A huge amount of teaching information is stored on the disk on the server, which can not be used or thrown away. How to convert a large amount of operable data into usable information and use this information for teaching evaluation has become a very key problem. Therefore, there is a need for a data processing method that can automatically discover and describe the association and implication between things.

This method can automatically mark the similarities and differences of data and predict the future development, which ensures the effective implementation of English teaching evaluation. In the following research, association rules are mainly used to mine English teaching data.

The implementation of data mining is divided into four steps: (1) summarize and sort out all the data of students’ teaching evaluation, extract relevant attributes, and clean the data. (2) According to the set code table, mine the cleaned data and the associated data in the teacher information base, extract the data mining object, and code it to generate the evaluation database. (3) According to the minimum support set by the decision-maker, the extracted transaction database is generated into frequent item sets by using association rules. (4) According to the minimum confidence of the set, construct association rules [11–13]. The implementation of the whole process will be analyzed in detail below.

Among the methods in data mining, association rule mining is a highly applied method, which can clarify the connection and association of different data items based on a lot of English teaching data.

The problem of association rule mining can be described as follows: Given a transaction database \( S \), represent the set of all items in the transaction database as \( A = \{a_1, a_2, \ldots, a_n\} \), where each transaction \( U \) contains at least one item in item set \( A \), namely, \( U \subseteq A \). Association rules are implicit expressions of the form \( P \Rightarrow Q \), where \( P \in A \), \( Q \in A \), and \( P \cap Q = \emptyset \) [14, 15].

In the transaction database, the percentage including both transaction \( P \) and transaction \( Q \) is the support degree of association rule \( S \), also known as probability. The formula is as follows:

\[
\text{Support}(P \Rightarrow Q) = H(P \cup Q).
\]

In the transaction database, the percentage including both transaction \( P \) and transaction \( Q \) is the confidence level of association rule \( S \), also known as probability. The formula is as follows:

\[
\text{Confidence}(P \Rightarrow Q) = H(Q|P).
\]

The set of \( k \) terms is called the item set \( k \). In the transaction database, if the item set’s occurrence frequency is greater than (including equal to) the product of minimum support threshold and all transactions, it can be regarded as frequent item set. Item set \( G_k \) represents the set of frequent item set \( k \).

Association rule mining involves two steps:

(Step 1) Clear and define total frequent item sets.
(Step 2) According frequent item sets, construct strong association rules.
(Step 3) Because the algorithm is elementary, therefore, the research of association rule mining mainly focuses on Step 1, which is the mining of frequent item sets of data sets.

The data items in the transaction database are represented by \( S \). If the data item \( S \) is covered in transaction \( W \), the value of transaction \( S \) is 1. If the data item \( S \) does not exist in transaction \( W \), the value of transaction \( S \) is 0.

The support count of data items is expressed by compression matrix:

\[
S_j = a_i \times b_j = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1i} \\ s_{21} & s_{22} & \cdots & s_{2i} \\ \vdots & \vdots & \ddots & \vdots \\ s_{i1} & s_{i2} & \cdots & s_{im} \end{bmatrix}.
\]

After the above transformation, it can calculate each data
item’s support degree in the matrix $S_i$:

$$P_c(S_i) = \sum_{i=1}^{n} (a_ib_j)^T \times \partial_{i} + D_k. \quad (4)$$

In the above formula, $\partial_{i}$ stands for support growth coefficient, and $D_k$ stands for information obtained during the support calculation process.

According to the algorithm based on the matrix for mining frequent item sets, after the transformation of formula (4), the support degree of $k$–item set in the matrix can be obtained.

$$P_c(S_iW_j) = \sum_{i=1}^{n} \left[ \alpha(S_i) \cdot y(W_j) \right]^2 \times K_{i}. \quad (5)$$

Among them, $x(S_i)$ represents the row vector corresponding to the item set; $y(W_j)$ represents the column vector corresponding to the item set; $K_{i}$ stands for the value multiplied by column vector and weight.

Based on the above analysis, the main algorithm steps of English teaching data mining based on association rules are as follows:

1. Data conversion converts transaction data into a compressed matrix form. Each row of the converted data matrix represents a transaction, and each column is the item set of the transaction. The same transaction is stored in the matrix only once, and an array is created to store the number of repetitions of the transaction to achieve compression of transaction data.

2. Set the item in the transaction data set $S$ as $S_i(i = 1, 2, m)$; calculate the support of each item according to formula (4). Compare the value of each item with the minimum support threshold. If the former is larger than the latter, filter it. After filtering, it can obtain the frequent item set [16, 17].

3. When screening frequent item sets in candidate frequent item sets, item sets need to be connected and support counting is carried out by using formula (4). If it is not less than the minimum support count, save the column vector.

4. Scan data line by line. If the number of the line vector whose value is 1 is less than or equal to 1, then delete the line, and the remaining line combination is $x(S_i)$.

5. Perform connection operation on the item set to be connected in $x(S_i)$, and make operation of support count of $k$–item set generated by connection according to formula (5). If it is not less than the minimum support count, save the column vector to $y(W_j)$. The item set corresponding to the finally retained column vector is the frequent item [18, 19].

2.2. Data Cleaning. The teaching data warehouse contains a large amount of data imported from various data sources. Their quality issues are one of the elements that restrict the effect of teaching data processing. Therefore, data cleaning technology needs to be applied to improve data quality before quantitative evaluation of teaching quality.

The identification and elimination of similar duplicate records is a key issue in data cleaning. To determine whether two records are the same entity, usually select representative fields such as name, ID number, and date of birth. After the fields are matched, the records composed of these fields are matched. In English teaching, the identification of the assignments submitted by students is usually describing the student’s student ID, name information, or a mixture of the two, which brings certain difficulties to data processing, which is mainly reflected in the separation and increase of repeated records. The complexity and execution time of the algorithm are discussed. This paper designs a teaching data cleaning model that can effectively detect repeated data, as shown in Figure 1.

The data similarity calculation in Figure 1 mainly includes five steps: (1) The teaching data is divided into numerical data and character data according to the data type. (2) The numerical precision matching method and the edit distance algorithm are used to calculate the similarity of each field degree. (3) Combine the fields, and the result calculated by the effective weight is the data similarity. (4) To judge the results, the user usually sets a threshold according to experience (e.g., 0.8, which can be adjusted dynamically). If the similarity of two records exceeds the threshold, it means that they are similar. (5) Cleaning similar data can not only reduce the data burden in the later teaching evaluation process but also improve the evaluation efficiency.

The process of data cleaning model of English teaching evaluation is shown in Figure 2.

3. Realization of English Teaching Evaluation

Combining with the preprocessing results of teaching information, the teaching evaluation index system can be designed. Analytic hierarchy process (AHP) can be used to construct evaluation index’s factor subset and also can acquired each evaluation index’s weight by constructing a judgment matrix. Therefore, big data fuzzy used the $K$-means clustering algorithm which constructs an English teaching evaluation model and realizes English teaching evaluation through this model [20–22].

3.1. Establishing the Evaluation Index System of English Teaching by AHP. The hierarchical structure is shown in Figure 3 [23, 24].

3.1.1. Establish the Evaluation Index Factor Set. After using analytic hierarchy process to carry out the above research, a set of English teaching evaluation factors can be formed [25, 26], and an English teaching evaluation system can be established in Table 1; the evaluation factor set $E$ can be
composed of 4 subelement sets:
\[ E = \{E_1, E_2, E_3, E_4\}. \]  

### 3.1.2. Constructing the Judgment Matrix

The judgment matrix is the basis of the weight ranking and has a decisive influence on the final total ranking. Therefore, when using analytic hierarchy process, the judgment matrix should be constructed first. To accurately construct the judgment matrix at all levels, it is necessary to conduct objective and detailed investigation, research, and analysis [27, 28].

When constructing the judgment matrix, must first make a pairwise comparison. At this time, must repeatedly answer: For a certain criterion \( E \), which of the two elements \( E_1 \) and \( E_2 \) is more important, how important it is, and the importance must be assigned a certain value. This is the proportional scale degree [29–31]. The AHP method uses a scale of 1-9.

Taking experts, teachers, and students as the research objects, carrying out in-depth questionnaire survey and unifying the investigation results, the corresponding judgment matrix can be established. In the hierarchical structure, the judgment matrix of primary index is expressed as matrix \( X \), and \( Y_1 \), \( Y_2 \), \( Y_3 \), and \( Y_4 \) are the judgment matrices of each second-level indicator against the upper-level indicator to which it belongs.

![Diagram](image.png)

**Figure 1: Teaching data cleaning model.**

**Figure 2: Data cleaning flow chart.**

**Figure 3: Hierarchical structure of analytic hierarchy process.**

\[
X = \begin{bmatrix}
1 & 2 & \frac{1}{2} & 1 \\
\frac{1}{2} & 2 & 1 & 1 \\
4 & 2 & 2 & 1 \\
1 & 2 & 1 & 1 \\
\end{bmatrix},
\]

\[
Y_1 = \begin{bmatrix}
1 & 2 & 1 \\
\frac{1}{2} & 2 & 1 \\
\frac{1}{2} & 2 & 1 \\
\end{bmatrix},
\]

\[
Y_2 = \begin{bmatrix}
1 & \frac{1}{2} & 2 & 2 \\
\frac{1}{3} & 1 & 1 & 2 \\
2 & 1 & 3 & 1 \\
1 & 1 & 1 & 2 \\
\end{bmatrix},
\]

\[
Y_3 = \begin{bmatrix}
1 & 1 & 2 \\
\frac{1}{2} & 1 & \frac{1}{2} \\
1 & 2 & 2 \\
\end{bmatrix},
\]
3.2. Establishment of English Teaching Ability Assessment Model

3.2.1. Establishment of Evaluation Index System

A comprehensive assessment system is established, including first-level indicators and secondary indicators. The first-level indicators are teaching practice, teaching methods, teaching effect, and teaching management. Secondary indicators include the teaching content matches the training standards for English majors, the teaching objectives are clear, and the curriculum is reasonable, theory and practice penetrate each other and combine organically, the teaching methods are diversified and meet the teaching needs, students organize students to carry out autonomous learning activities and give targeted guidance and help, the teaching management system is relatively sound, which strictly limits the responsibilities of teachers in different teaching links, comprehensive teaching management information, and ability to assess the quality of teaching on a regular basis.

Table 1: The table of English teaching evaluation index system.

| First level indicator | Secondary indicators |
|-----------------------|-----------------------|
| E1 teaching practice  | E11 the teaching content matches the training standards for English majors |
|                       | E12 the teaching objectives are clear, and the curriculum is reasonable |
|                       | E13 theory and practice penetrate each other and combine organically |
|                       | E14 the teaching methods are diversified and meet the teaching needs |
| E2 teaching methods    | E21 students have a solid grasp of English knowledge |
|                       | E22 teachers organize students to carry out autonomous learning activities and give targeted guidance and help |
|                       | E23 students can complete learning tasks independently |
|                       | E24 emphasize the cultivation of students’ comprehensive study ability |
| E3 teaching effect     | E31 the assessment level has been significantly improved |
|                       | E32 students have a solid grasp of English knowledge |
|                       | E33 the assessment level has been significantly improved |
| E4 teaching management| E41 the teaching management system is relatively sound, which strictly limits the responsibilities of teachers in different teaching links |
|                       | E42 comprehensive teaching management information |
|                       | E43 ability to assess the quality of teaching on a regular basis |

\[ Y_k = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 2 & 1 & 2 \end{bmatrix} \]  \hspace{1cm} (11)

According to the above scaling rules, the judgment matrix is obtained:

\[ X_{ij} = (Y_{ij})_{n \times m}, \]  \hspace{1cm} (12)

Among them, \( Y_{ij} = 1/Y_{ji} \). In the process of determining \( Y_{ij} \), the method of multiple polling is used, and experts are consulted to obtain \( Y_{ij} \) (i < j) according to the scale comparison method in Table 2, that is, the importance of \( y_i \) relative to the \( y_j \) factor, and the relative importance scale value between the two factors is given; count the values given by the experts, and obtain the final value by the Delphi method. Therefore, in the English teaching evaluation, AHP can be used to avoid large deviation in the weight coefficient of English teaching evaluation index caused by subjective factors such as the limitation of the expert’s professional background.

3.2.1.1. Evaluation Index Weights

According to evaluation index factor which is established in Section 3.1.1, combined with the judgment matrix established by the analytic hierarchy process, the index weights at all levels are obtained. Table 2 shows the weights of English teaching evaluation index.

3.2.1.2. Establishment of English Teaching Ability Assessment Model

3.2.1.2.1. Establishment of English Teaching Ability Assessment Model

The new English teaching evaluation method proposed by this study can effectively transform teaching evaluation into simpler question that is aimed at the K-means clustering objective function, to carry out the least square estimation.

The entropy-based feature extraction value can be obtained for the teaching evaluation constraint feature data.

\[ R_{loss} = 1 - \frac{1 - \tau_c}{p_c} + \frac{r_c - r_w}{p_c}. \] \hspace{1cm} (13)

Among them, \( \tau_c \) represents multiscale information entropy; \( p_c \) represents feature vector; \( r_c \) represents entropy value function; \( r_w \) represents entropy value change function.

If the disturbance feature vector of English teaching evaluation is expressed as \( p_z \), the estimation formula is replaced by the least square solution:

\[ h_{p} = a(t) + b(t) = [a(t)p_z]^T. \] \hspace{1cm} (14)

Among them, \( a(t) \) and \( b(t) \) are, respectively, used to represent the time series and constraint index series, which are used to evaluate data distribution and teaching quality, respectively.
Table 2: Weights of English teaching evaluation index.

| First level indicator | Secondary indicators |
|-----------------------|----------------------|
| $E_1$ teaching practice | $E_{11} = 0.37$ |
|                       | $E_{12} = 0.25$ |
|                       | $E_{13} = 0.38$ |
| $E_1$ teaching method  | $E_{14} = 0.31$ |
|                       | $E_{15} = 0.47$ |
| $E_1$ teaching effect  | $E_{16} = 0.26$ |
|                       | $E_{17} = 0.27$ |
| $E_1$ teaching management | $E_{18} = 0.10$ |
|                       | $E_{19} = 0.52$ |
|                       | $E_{20} = 0.38$ |

Under the method of data translation, the amplitude of change of English teaching ability can be randomly processed to obtain $a^t(c)$. In view of the data obtained from the empirical research on English teaching evaluation in set $c$, the utilization rate of teaching resource allocation can be calculated by the following formula:

$$\varepsilon_p = \frac{(P_0 - P_1)\mu_p}{\alpha_c}.$$  \hspace{1cm} (15)

Among them, $P_0$ represents the resource concentration factor; $P_1$ represents the resource dispersion factor.

For the sake of solving the similar problems of English teaching resource distribution, the fuzzy nearness filling method can be used to solve them [35]:

$$\text{sim}(\rho_0, \rho_1) = \sum_{j=1}^{n} \left( \frac{1}{\bar{\delta}_0 - \bar{\delta}_1} \right)^{2} \epsilon_p$$  \hspace{1cm} (16)

Among them, $\bar{\delta}_0$ and $\bar{\delta}_1$ are used to represent the eigenvectors of prior distributions and clustering center vector of $K$-means algorithm, respectively.

In the process of integrating and clustering English teaching evaluation index parameters, the feature fusion method should be applied. Formula (17) is the integration of English teaching resource output.

$$D_p = \sum_{i=1}^{n} \log_2 P_i$$  \hspace{1cm} (17)

Among them, $P_i$ represents the quantitative recursive feature. Assuming that $P_1 < M$ exists in the quantitative recursion feature, the probability density feature of the distribution of English teaching resources is calculated as

$$\rho_p = \frac{P}{2} \sqrt{A_{\rho}}.$$  \hspace{1cm} (18)

The big data flow $\eta$ of English teaching evaluation is divided into submatrices $N_{ij}$ with quantity and size of $m$ and $N_{ij,m}$ respectively. After the operation of cluster analysis and integration of the index parameters, a reasonable teaching resource allocation scheme can be developed to facilitate the implementation of teaching evaluation activities.

4. Simulation Experiment Verification

When studying the effectiveness of this evaluation method, the corresponding evaluation methods in References [8, 9] can be used for comparative analysis, and the accuracy of evaluation results under different teaching evaluation methods can be compared in detail. Among them, Reference [8] adopts the teaching evaluation method under grey correlation analysis and neural network, while Reference [9] adopts the teaching quality evaluation model under a data mining algorithm.

4.1. Experiment Preparation. Relevant research data are from the English teaching evaluation by college students at the end of the term. The evaluation questionnaire is self-edited by the school and contains 13 indicators, which are divided into four factors: teaching practice, teaching method, teaching effect, and teaching management. The scale uses a five-level score of 5 to 1, which, respectively, represent “good but poor.” Based on the above survey data, the evaluation effects of different methods are compared and calculated and processed the experimental result data by MATLAB software, in order to ensure the accuracy of the experimental results.

4.2. Analysis of Experimental Results
4.2.1. Evaluation Result Error. Generally, the actual evaluation results are different from the expected results, which will lead to poor accuracy of the evaluation results; it indicates that different evaluation methods will make the evaluation index system imperfect and the index weight obtained is not accurate enough. Therefore, according to the evaluation data of English teaching feedback from students, a comparative analysis was conducted on the evaluation error between the evaluation method in references [8, 9] and the evaluation method in this study, as shown in Figure 4.

Combined with Figure 4, it can be found that the teaching evaluation method constructed in this study can significantly reduce the error of evaluation results, and the error is always less than 6%, and the maximum value is about 5%; the teaching evaluation effect of Reference [8]’s method and Reference [9]’s method is poor, and the maximum error

![Figure 5: Comparison results of evaluation time.](image1)

![Figure 6: Comparison result of evaluation data processing effect.](image2)
is 14% and 11%, respectively, indicating that the traditional method can not obtain the ideal teaching evaluation results. By analyzing the research results, it can be found that the evaluation method in this study has great advantages. Compared with other evaluation methods, the method in this study can also show that the accuracy is quite high, and greatly reduced error also has important utilization value in English teaching evaluation.

4.2.2. Time-Consuming Evaluation. Teaching evaluation time-consuming corresponds to the evaluation performance and evaluation rate of different methods. Under different English teaching evaluation methods, the final evaluation effect will improve with the shortening of evaluation time. Comparative analysis was conducted between the evaluation method of this study and that of References [8, 9] to observe the difference in evaluation time. The comparison results are shown in Figure 5.

Combined with Figure 5, it was shown that while the teaching data increases sharply, the time required for each teaching evaluation method is significantly prolonged. Among them, the teaching evaluation time consumption of Reference [8]’s method is before the teaching data is less than 300 MB. The increasing trend of time is relatively slow. After reaching 300 MB, the increasing trend of time-consuming teaching evaluation increases rapidly, while the teaching evaluation time of Reference [9]’s method has always maintained a significant growth trend. According to the specific data results, the maximum teaching evaluation time of the method of this article is 3.9 s, the maximum teaching evaluation time of Reference [8]’s method is 13.1 s, and the maximum teaching evaluation time of Reference [9]’s method is 15.3 s. The change trend and specific data prove the advantages of the method in this article in the time-consuming aspect of English teaching evaluation.

4.2.3. Evaluate the Effect of Data Processing. Due to the rise of new teaching models such as network teaching, English teaching data will continue to increase, which will inevitably affect the results of English teaching evaluation. For example, only part of the data is processed, some important data is ignored, and the data will be repeated. Utilization, causing double counting. Therefore, a large amount of evaluation data processing effects are used as experimental indicators to compare different methods. The comparison results are as shown in Figure 6.

It can be seen from Figure 6 that during the fourth iteration, the method of this article can effectively process the teaching evaluation data, while Reference [8]’s method and Reference [9]’s method can process the teaching evaluation data only when the number of iterations is 6 and 7, respectively. Combined with the comparative analysis results, it is found that this method can process a lot of English teaching data efficiently and timely, which indicates that this evaluation method has a good effectiveness.

5. Conclusion

The innovation of English teaching evaluation system based on the fuzzy K-means clustering algorithm and the construction of English teaching evaluation model can ensure the accuracy and scientificty of final evaluation results, solve the shortcomings of traditional teaching evaluation model, make the whole process evaluation of English teaching into reality, and improve the scientific and standardized level of English teaching quality management. With the help of the English teaching evaluation model based on the fuzzy K-means clustering algorithm, college leaders and teachers can better analyze and check the English teaching situation, facilitate the timely development of English teaching problems, formulate targeted solutions, and optimize English teaching programs. This teaching evaluation method can realize the hierarchical and multangle three-dimensional evaluation of college English teaching and can reflect the teaching ability of English teachers. The English teaching evaluation method based on the fuzzy K-means clustering algorithm gives full play to the advantages of advanced network information technology, which can evaluate and analyze English teaching data more quickly, accurately, and conveniently. This evaluation method has good scientificity, real time, and practicability and avoids the problem of large error of the traditional evaluation model. The evaluation method of English teaching in this study integrates qualitative and quantitative analysis, realizes scientific and objective evaluation of English teaching, clarifies the direction of English teaching reform, and effectively improves the overall quality of English teaching.

Data Availability

The author can provide all the original data involved in the research.

Conflicts of Interest

The author indicates that there was no conflict of interest in the study.

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