Retraction

Retracted: A Method of Monitoring and Evaluating the Quality of English Classroom Teaching Based on Big Data

Mobile Information Systems

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Peer-review manipulation

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.

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] R. Wang, "A Method of Monitoring and Evaluating the Quality of English Classroom Teaching Based on Big Data," *Mobile Information Systems*, vol. 2022, Article ID 7957878, 10 pages, 2022.

Research Article

A Method of Monitoring and Evaluating the Quality of English Classroom Teaching Based on Big Data

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To improve the reliability and accuracy of quality of English instruction in the classroom monitoring and assessment, as well as to reduce the time spent monitoring and evaluating the quality of English instruction in the classroom, a big data-based approach to monitor and evaluate the quality of English instruction in the classroom is proposed. A frequent itemset mining technique for quality of English instruction in the classroom monitoring data is built based on a study of the theoretical basis of big data and the features of quality of English instruction in the classroom monitoring data. To complete the data transformation of quality of English instruction in the classroom monitoring, the multivalued continuous attribute is quantified and turned into a two-dimensional Boolean data matrix. To mine the frequent itemsets of quality of English instruction in the classroom monitoring data, a frequent itemset mining algorithm based on the compressed matrix is applied. This work creates a quality of English instruction in the classroom evaluation model using the gray correlation method of multiobjective decision-making and weighted gray correlation analysis to realize the monitoring and evaluation of quality of English instruction in the classroom. The experimental results suggest that the proposed method is highly reliable and accurate and that it can significantly reduce the time spent monitoring and evaluating the quality of English classroom instruction.

1. Introduction

Teaching quality is an eternal theme in the development of education. It is not only the foundation of colleges and universities but also the lifeline of the school's survival and development [1]. As the educational concept becomes more commonly acknowledged and practiced in the education community, increased expectations are placed on the quality of classroom teaching by teachers. In today's colleges and universities, English classroom instruction is the most common method of instruction. It is the foundation of teacher instruction and plays a critical role in the learning process [2]. The research on the monitoring and assessment of quality of English instruction in the classroom is not only beneficial to the development of English classroom teaching theory in colleges and universities, but it also helps to improve the quality of English classroom teaching and also can ensure the smooth progress of quality of English instruction in the classroom assessment and the effective role of English classroom teaching activities. Improving the quality

of English classroom instruction is not only an essential demand of the current curriculum reform's deeper development but also a necessary development trend of evaluation system reform, as well as the actual request of the English classroom [3]. As a result, the research on the development and evaluation of quality of English instruction in the classroom monitoring system contributes to the improvement of quality of English instruction in the classroom.

At present, relevant scholars in this field have researched teaching quality monitoring and evaluation and have achieved certain research results. Reference [4] proposed a method for evaluating college quality of English instruction in the classroom based on triangular fuzzy numbers. The nonlinearity and fuzziness of evaluation parameters are taken into account when using the triangular fuzzy number evaluation approach based on the analytic hierarchy process to assess instructional quality. To acquire more objective evaluation results of teachers' classroom teaching quality, it is critical to scientifically determine the weight value of each evaluation indicator and combine qualitative and

quantitative evaluations in the real teaching quality evaluation process. Reference [5] developed a preference selection index-based fuzzy evaluation approach for college English teaching quality. This work develops a college English assessment index system that employs linguistic terminology, triangular fuzzy numbers, and the preference selection index method to evaluate teachers' teaching quality thoroughly. The findings of the comprehensive evaluation are outstanding, and the nonlinearity and fuzziness of the evaluation criteria are properly taken into account. However, the aforesaid methodologies still have issues with low reliability and accuracy, as well as a long period of monitoring and evaluation of teaching quality.

In response to the aforementioned issues, this research proposes a big data-based monitoring and evaluation strategy for quality of English instruction in the classroom. A frequent itemset mining technique for quality of English instruction in the classroom monitoring data was developed based on big data theory and the peculiarities of quality of English instruction in the classroom monitoring data. The frequent itemsets of quality of English instruction in the classroom monitoring data are mined through the transformation of quality of English instruction in the classroom monitoring data, and the quality of English instruction in the classroom evaluation model is constructed to realize quality of English instruction in the classroom monitoring and evaluation. This strategy may successfully improve the reliability and accuracy of quality of English instruction in the classroom monitoring and evaluation, as well as reduce the amount of time it takes to do so.

The rest of the paper is organized as follows: Section 2 provides the theoretical basis of big data, in which we will discuss data mining, association rule mining, frequent itemset mining algorithm based on the compressed matrix, gray correlation method for multiobjective decision-making, and weighted gray correlation analysis; Section 3 gives monitoring and evaluation methods of quality of English instruction in the classroom in which we will discuss the transformation of monitoring data of quality of English instruction in the classroom, frequent itemset mining of quality of English instruction in the classroom monitoring data, and the evaluation model of quality of English instruction in the classroom; Section 4 gives experimental environment and data, quality of English instruction in the classroom monitoring and evaluation reliability, quality of English instruction in the classroom monitoring and assessment accuracy, and monitoring and evaluation time of quality of English instruction in the classroom; and conclusion is discussed in Section 5.

2. Theoretical Basis of Big Data

The mining and analysis of massive amounts of data to obtain high-value services and goods are known as big data [6]. General databases are unable to obtain or process data collections. At the same time, it should be noted that big data does not always necessitate a large volume of data to reach the TB level. With the public's growing awareness of big data, the 5V qualities of big data, namely, volume, variety, velocity, veracity, and value, are now widely recognized. The 5V characteristics of big data are presented in Figure 1.

Education big data is a subset of big data that pertains to data created in the educational field. Education big data generates a vast amount of relevant data during the educational process. It can collect static and dynamic data in the whole education process. Compared with the traditional stage sex education big data, it has more powerful comprehensiveness and timeliness. The arrival of the era of big data makes education evaluation more diversified.

2.1. Data Mining. The process of extracting hidden and potentially valuable knowledge and information from random, fuzzy, noisy, and large amounts of data is known as data mining [7]. There are three stages to data mining: data pretreatment, data mining, and result evaluation. Figure 2 depicts the data mining procedure.

(1) Data preprocessing stage: because the data stored in the computer system database has problems such as noise, data missing, and redundancy, it is not suitable for direct data analysis and mining. Therefore, it is necessary to further preprocess the original data, and the quality of preprocessing directly affects the quality of data mining results. In the data preprocessing stage, data cleaning, integration, reduction, transformation, and other steps need to be carried out. Finally, the preprocessed data should have the characteristics of accuracy, integrity, and consistency

(2) Data mining stage: data mining stage is the key stage of the whole data mining process. The purpose is to mine and analyze the preprocessed data. At this stage, it is very important to clarify the mining task and select the mining algorithm. The mining task should be defined in combination with the user's needs. After determining the task requirements, use the data features to select the appropriate mining methods, such as clustering, association, and classification, and then use the corresponding mining means to mine the preprocessed data to obtain the corresponding knowledge and patterns

(3) Result evaluation: after the previous data mining stage, the corresponding results will be obtained. However, whether the mined knowledge is effective still needs to be analyzed and evaluated to eliminate redundant and irrelevant results and finally get useful information. If the mined information is not what we need, we need to return to the previous stage, reselect data, adjust parameters, and even change the data mining method. Finally, when trying to get meaningful results, we need to further convert the results into a way that users can easily understand

2.2. Association Rule Mining

2.2.1. Basic Concepts of Association Rule Mining. One of the most essential research methodologies in data mining is association rule mining [8]. The purpose of association rule
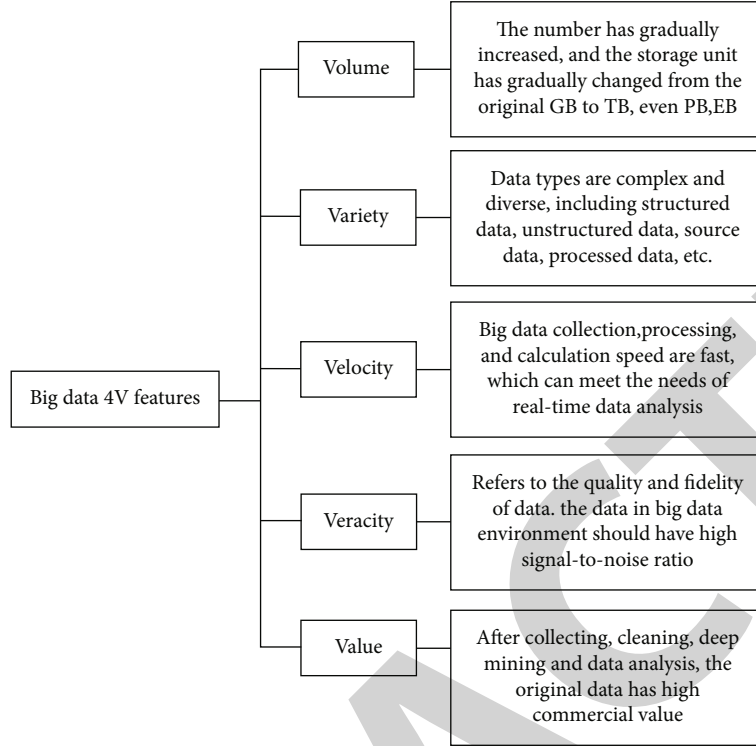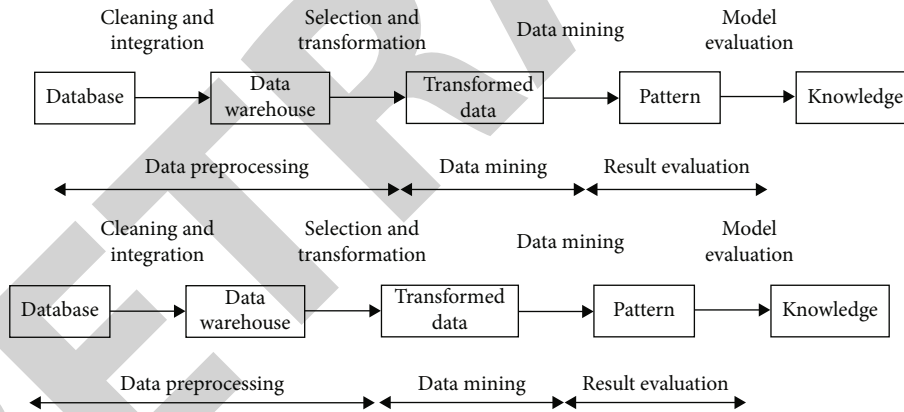
FIGURE 1: 5V characteristics of big data.

FIGURE 2: Data mining flowchart.

mining is to discover relevant connections or related relationships between data elements from a huge dataset. The following is a description of the problem of association rule mining. If you have a transaction database Z, let $X = (x_1, x_2, \cdots, x_m)$ be the set of all items in the transaction database, where each transaction C contains at least one item in the itemset X, namely, $C \subseteq X$. Association rules are implicit expressions of the form $M \Rightarrow N$, where $M \subset X$, $N \subset X$, and $M \cap N = \varnothing$. The support degree of association rules in Z is the percentage of transactions that also contain M, N in the transaction database, that is, the probability is expressed as

$$\text{support}(M \Rightarrow N) = P(M \cup N). \tag{1}$$

The confidence of the association rule in Z is the percentage of transactions that also include N when the transaction database already contains M, that is, the conditional probability is expressed as

$$\text{confidence}(M \Rightarrow N) = P(N|M). \tag{2}$$

An itemset is a group of related items. An itemset with k items is referred to as a k itemset. The frequent itemset V_k is defined as the itemset with a frequency of occurrence more than or equal to the product of the minimum support threshold and the total number of transactions in the transaction database. The itemsets are a collection of frequently occurring k itemsets. There are two steps to mining association rules.

Step 1. Identity all often occurring itemsets.

Step 2. Develop strong association rules based on frequently occurring itemsets.

The algorithm of Step 2 is relatively simple, so the research of association rule mining mainly focuses on the first step, that is, the mining of frequent itemsets in datasets.

2.2.2. Association Rule Mining-Related Attributes

Property 1. All nonempty subsets of frequent itemsets are also frequent itemsets [9].

Corollary 1. B_k *is a frequent k itemset of the dataset Z, so* V_{k-1} *must contain k subsets of* $k-1$ *items of* B_k.

Corollary 2. *When the number of items in the frequent k itemset is greater than k, it is possible to connect to generate frequent* $k+1$ *itemsets.*

Property 2. Itemsets generated by connection of infrequent itemsets are also infrequent itemsets.

Property 3. A transaction that does not include frequent k itemsets must not include any frequent $k+1$ itemsets.

Theorem 1. *The database contains a transaction whose number of items is k, and it must not contain any frequent itemsets whose number of items is greater than k.*

Theorem 2. *If the first* $k-2$ *items of two* $k+1$ *itemsets are any different, then the itemset generated by the connection is either duplicated with other itemsets or infrequent itemsets.*

2.3. Frequent Itemset Mining Algorithm Based on Compressed Matrix.
Using a compressed matrix, the frequent itemset mining technique converts transaction data into a compressed two-dimensional Boolean matrix [10]. To store the number of transaction occurrences, compress the transaction data, maintain only one of the identical transaction data, and increase the weight array ϑ Second, the compressed transaction data is transformed into a two-dimensional Boolean matrix according to the definition below.

Let X_i represent a data item in the transaction database. If the data item X_i is contained in the transaction C_j, then the value of X_i is 1 in the transaction. If the data item X_i is not included in the transaction C_j, then the value of X_i is 0 in the transaction. Based on the frequent itemset mining algorithm of the compressed matrix, the support count of each data item X_i in the transformed Boolean matrix τ is expressed as

$$\text{support\_count}(X_i) = \sum_{j}^{n} C_j \vartheta. \tag{3}$$

Based on the frequent itemset mining algorithm of the compressed matrix, the support count of k itemsets in the transformed Boolean matrix τ is expressed as

$$\text{support\_count}(X_i X_j) = (L_i \wedge L_j)\vartheta. \tag{4}$$

In formula (4), L_i is the column vector corresponding to the itemset, and L_j is the column vector obtained after the logical AND. The algorithm flow of frequent itemset mining based on the compressed matrix is as follows.

Step 1. Data conversion is in which the transaction data is compressed into a two-dimensional Boolean matrix. Each transaction is represented by a row in the converted data matrix, and each itemset is represented by a column. The same transaction is only saved in the matrix once, and the array ϑ is set up to store the number of times the transaction has been repeated, allowing the transaction data to be compressed.

Step 2. Set the item X_i in the transaction dataset Z as the frequent 1 itemset, compute the support of each item using formula (3), filter out items greater than the minimum support threshold, and get V_1.

Step 3. Pairwise connect the items in the V_1 itemset, and use a formula to get the support count of the 2 itemsets created by the connection (4). Save the column vector τ_2 if it is not less than the minimum support count. Finally, matrix τ_2 is obtained, and the matrix τ_2 column vector represents frequent 2 itemsets [11]. Steps 4 and 5 are repeated when $k \geq 2$ is used.

Step 4. Scan the data one line at a time. Delete the line if the number of lines whose value is 1 is fewer than or equal to 1. τ_{K1} is the final row combination.

Step 5. Perform a connection operation on the itemsets to be connected in τ_{K1}, and calculate the support count of the $k+1$ itemsets generated by the connection according to formula (4). If it is not less than the minimum support count, save the column vector to τ_{K+1}. The itemset corresponding to the finally retained column vector is frequent $k+1$ item V_{K+1}.

2.4. Gray Correlation Method for Multiobjective Decision-Making.
Suppose that the set of multi-index decision domain objects is $Q = \{Q_1, Q_2, \cdots, Q_n\}$, the set of factor indicators is $W = \{W_1, W_2, \cdots, W_m\}$, and the attribute value of the object Q_i to indicator W_j is denoted as $e_{ij}(i = 1, 2, \cdots, n; j = 1, 2, \cdots, m)$. Thus, the initial model can be generated, that is, the index matrix is

$$W = |e_{ij}|. \tag{5}$$

The basic idea of the model is outside the overall evaluation object, virtualize a standard object, and take the closeness between the evaluated object and the standard object as the evaluation standard. Those with high closeness to the standard object are better than those with low closeness to the standard object. Therefore, through this model, we can find the best object and the order of each object.

The method of removing all data of a sequence with its first number to obtain a new sequence is called initialization processing. This series has a common starting point, dimensionless, and its data values are greater than 0. Let $t_{ij} = \chi(s_{0j}, s_{ij})$ and χ be a specific relevance map, and t_{ij} is the relevance

degree of the child factor $s_{ij}(i = 1, 2, \cdots, n; j = 1, 2, \cdots, m)$ to the parent factor $s_{0j}(j = 1, 2, \cdots, m)$. Then, there are

$$t_{ij} = \frac{\min\limits_{n}\min\limits_{m}\left|s_{0j} - s_{ij}\right| + \delta}{\left|s_{0j} - s_{ij}\right|\delta}. \tag{6}$$

In formula (6), δ is the resolution coefficient, and its function is to adjust the size of the comparison environment, that is, to reduce the comparison environment. When $\delta = 0$, the environment disappears. When $\delta = 1$, the environment remains unchanged. $\delta = 0.5$ is usually taken. The matrix A $(t_{ij})_{n\times m}$ composed of $n \times m$ gray incidence degrees $t_{ij}(i = 1, 2, \cdots, n; j = 1, 2, \cdots, m)$ is called the multiobjective gray incidence judgment matrix [12], namely,

$$A = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1m} \\ t_{21} & t_{22} & \cdots & t_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ t_{n1} & t_{n2} & \cdots & t_{nm} \end{bmatrix}. \tag{7}$$

2.5. Weighted Gray Correlation Analysis. Establish a weighted gray correlation analysis algorithm [13], and the specific steps are as follows.

(1) According to the given set of objects and indicators, assuming that q indicators are used to evaluate p objects, the matrix O is constructed as follows:

$$O = \begin{bmatrix} o_{11} & o_{12} & \cdots & o_{1q} \\ o_{21} & o_{22} & \cdots & o_{2q} \\ \cdots & \cdots & \cdots & \cdots \\ o_{p1} & o_{p2} & \cdots & o_{pq} \end{bmatrix}. \tag{8}$$

(2) According to the requirements of the evaluation, set the index value of the standard object. Suppose its specific value is $o_{01}, o_{02}, \cdots, o_{0q}$, and the matrix U is constructed as follows:

$$U = \begin{bmatrix} o_{01} & o_{02} & \cdots & o_{0q} \\ o_{11} & o_{12} & \cdots & o_{1q} \\ o_{21} & o_{22} & \cdots & o_{2q} \\ \cdots & \cdots & \cdots & \cdots \\ & o_{p1} o_{p2} & \cdots o_{pq} \end{bmatrix}. \tag{9}$$

(3) Since the above indicators may have different dimensions, to eliminate the influence of dimensions, the

evaluation indicators should be dimensionless before evaluation [14]. That is, the matrix U is initialized, and the generated matrix Y is as follows:

$$Y = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ y_{11} & y_{12} & \cdots & y_{1q} \\ y_{21} & y_{22} & \cdots & y_{2q} \\ \cdots & \cdots & \cdots & \cdots \\ y_{p1} & y_{p2} & \cdots & y_{pq} \end{bmatrix}. \tag{10}$$

(4) Determine the weighting vector $\bar{\omega} = (\omega_1, \omega_2, \cdots, \omega_q)^T > 0$ between the evaluation indicators. The determination method can be divided into subjective and objective methods according to the specific situation. The objective determination of the weighted vector value is mainly based on the following.

Considering that $t_{1q}, t_{2q}, \cdots, t_{pq}$ is a gray-scale correlation of p objects to the q index with s_{0j} as the mother factor and $s_{pq}(p = 1, 2, \cdots, n; q = 1, 2, \cdots, m)$ as the child factor. They reflect the degree of correlation between the q actual factor value of each object and the ideal value, so the average value is expressed as

$$\mu_q = \frac{1}{p}\sum_{p=1}^{p} s_{pq}(q = 1, 2, \cdots, m). \tag{11}$$

It can reflect the proportion of the q indicator in the entire indicator space. Normalize $\mu_q(q = 1, 2, \cdots, m)$ to obtain $\omega_q = \mu_q / \sum_{q=1}^{m} \mu_q(q = 1, 2, \cdots, m)$, and then, $\bar{\omega} = (\omega_1, \omega_2, \cdots, \omega_q)^T$ can be used as the weight of the indicator.

(5) Under the action of the weighted vector $\bar{\omega}$, an augmented matrix is constructed, which is a weighted gray relational decision matrix A' expressed as

$$A' = \begin{bmatrix} \omega_1 t_{11} & \omega_2 t_{12} & \cdots & \omega_m t_{1m} \\ \omega_1 t_{21} & \omega_2 t_{22} & \cdots & \omega_m t_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ \omega_1 t_{n1} & \omega_2 t_{n2} & \cdots & \omega_m t_{nm} \end{bmatrix}. \tag{12}$$

(6) Calculate the comprehensive evaluation value $\psi_i = \sum_{q=1}^{m} \omega_q s_{pq}$. The larger the ψ_i value, the higher the closeness of the object p and the standard object p_b. At the same time, the order of ψ_i superiority and inferiority can be drawn

3. Monitoring and Evaluation Methods of Quality of English Instruction in the Classroom

This paper develops an algorithm for mining frequent itemsets of quality of English instruction in the classroom monitoring data using the characteristics of quality of English instruction in the classroom monitoring data. The algorithm's main goal is to turn the multivalued continuous property into a two-dimensional Boolean data matrix. The frequent itemset mining algorithm, which is based on the compressed matrix, is then used to mine the data matrix's frequent itemsets, and the connection steps are improved. Before connecting, judge whether the connection conditions are met. If it is satisfied, the connection will be carried out. If it is not satisfied, the corresponding connection operation will not be carried out, that is, there is no need to carry out the corresponding "and" operation, which avoids invalid calculation and reduces the calculation time.

3.1. Transformation of Monitoring Data of Quality of English Instruction in the Classroom. The following approaches are used to convert the transaction data into a compressed two-dimensional Boolean data matrix.

Increase the weight array and store the number of recurring transactions by compressing the transaction data, keeping only one recurring transaction, increasing the weight array ϑ; Table 1 shows the monitoring statistics for quality of English instruction in the classroom.

In Table 1, $H1$, $H2$, and $H3$ represent three monitoring indicators, respectively. There are five values of the three monitoring indicators (1 failed, 2 passed, 3 medium, 4 good, and 5 excellent). G1, G2, G3, G4, and G5 are five teaching evaluation data. The results of compressing the original quality of English instruction in the classroom monitoring data are shown in Table 2.

According to the following definition, the conversion of the original multivalued attribute dataset Z to a single-dimensional Boolean matrix τ_1 is realized.

The item B_i containing n attribute values is transformed into an itemset $B_1, B_2, \cdots, B_i, \cdots, B_n$. For item code B_i, B represents the group number, i represents the serial number within the group, and each item code B_i can represent a value of an item. When the value of B_i is 1, it means that B_i takes the attribute value corresponding to the serial number i in the group. When the value of B_i is 0, it means that B_i does not take the attribute value corresponding to the serial number in the group.

For example, the monitoring data of quality of English instruction in the classroom in Table 1 is converted. The monitoring data of quality of English instruction in the classroom is composed of three monitoring items. The values of each monitoring item are 5 excellent, 4 good, 3 medium, 2 passes, and 1 fail. Use the above definition to convert the data into a Boolean matrix of units.

First, create a new item code. The item code is made up of two numbers: a group number and an intragroup serial number. The intragroup serial number represents which value in the item, whereas the group number represents

Table 1: Monitoring data of quality of English instruction in the classroom.

	$H1$	$H2$	$H3$
G1	5 excellent	4 good	5 excellent
G2	4 good	5 excellent	3 medium
G3	5 excellent	4 good	5 excellent
G4	4 good	5 excellent	3 medium
G5	3 medium	4 good	4 good

Table 2: Monitoring data of quality of English instruction in the classroom after compression.

$H1$	$H2$	$H3$	ϑ
5 excellent	4 good	5 excellent	2
4 good	5 excellent	3 medium	2
3 medium	4 good	4 good	1

which group the item belongs to. The group number assigned to "$H1$" is A, "$H2$" is B, and "$H3$" is C, and the five values of each monitoring item 5 excellent, 4 good, 3 medium, 2 pass, and 1 fail are assigned group serial numbers 1, 2, 3, 4, and 5, respectively. Then, the original data items $H1$, $H2$, and $H3$ are recoded as $A1$, $A2$, $A3$, $A4$, $A5$, $B1$, $B2$, $B3$, $B4$, $B5$, $C1$, $C2$, $C3$, $C4$, and $C5$. For example, in the first row of transaction data, $H1$ is 5 excellent, so $A5$ is 1, $H2$ is 4 good, so $B4$ is 1, $H3$ is 5 excellent, and $C5$ is 1. The two-dimensional Boolean matrix results of the transformation of the compressed quality of English instruction in the classroom monitoring data are shown in Table 3.

3.2. Frequent Itemset Mining of Quality of English Instruction in the Classroom Monitoring Data. Increase the array C: record the number of 1s in each column; increase the array R: count the number of 1s in each row; increase the array it_k, which is used to store the code of the itemset corresponding to the column vector of the data matrix τ_K. The main process of frequent itemsets mining on multivalue attribute monitoring data is as follows.

Step 1. Make a lot of 1 itemsets. Calculate each item's support using formula (3), and then, filter away the items that are bigger than the minimum support level to produce the V_1 set, which is the most common 1 itemset. The value of the data item of the related item is recorded in the data matrix it_k, and the item code corresponding to the selected item is saved in the array τ_1.

Step 2. Make a pairwise connection decision on the data in τ_1 based on the item code in the it_k array. The two columns of data are logically operated bit by bit and multiplied bit by bit with the ϑ array. The support count of the 2 itemset formed by the new connection is the weighted sum. The column vector data is stored in the matrix τ_2 if the support count fulfills the minimum support requirement. V_2 is the itemset that corresponds to the column vector of the matrix τ_2 that was finally obtained. Make changes to arrays C and R. Repeat Steps 3 and 4 until you reach $k \geq 2$.

TABLE 3: Two-dimensional Boolean matrix of compressed quality of English instruction in the classroom monitoring data conversion.

	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	C1	C2	C3	C4	C5	ϑ
H1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	2
H2	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	2
H3	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	1

Step 3 (compression step). If the value of array R is less than or equal to 1, the related transaction contains only 1 or 0 frequent k itemsets. Delete the row vector and update the values of R array, C array, and ϑ array according to Property 3 and Theorem 1. Delete the row vector and update the values of R array, C array, and ϑ array, according to Property 3 and Theorem 1. If the value of array C is 0, it signifies that the result of a logical AND operation between the itemset and any other itemset is 0, and thus, it is impossible to connect with other itemsets to build frequent $k + 1$ itemsets, so delete the column vector. R and C array values should be updated. The item code corresponding to the remaining row combination is τ'_K, and the item code corresponding to the τ'_K column vector is stored in it_k.

Step 4. Connect steps to generate $k + 1$ itemsets frequently. To construct frequent $k + 1$ itemsets, the connection operation is done on the data of τ'_K. Before joining two often occurring k itemsets, check to see if the connection conditions are met using the it_k array. The connection conditions are met and the corresponding data items are connected if the item codes of the first $k - 1$ item of the item codes of the two k itemsets to be connected are the same and the group numbers of the item codes of the k item are different. The connection operation will not be completed if this connection requirement is not met.

3.3. Evaluation Model of Quality of English Instruction in the Classroom. In the monitoring and evaluation of quality of English instruction in the classroom, the weighted gray correlation analysis algorithm [15] is used to set the reference index value for quality of English instruction in the classroom evaluation, as follows.

(1) According to the five explanations and four index sets given, construct the matrices O and U as follows:

$$O = \begin{bmatrix} 0.62 & 0.36 & 0.72 & 0.36 \\ 0.85 & 0.12 & 0.36 & 0.06 \\ 0.72 & 0.26 & 0.68 & 0.36 \\ 0.75 & 0.43 & 0.79 & 0.22 \\ 0.80 & 0.35 & 0.42 & 0.21 \end{bmatrix},$$

$$U = \begin{bmatrix} 0.63 & 0.48 & 0.79 & 0.41 \\ 0.65 & 0.32 & 0.68 & 0.39 \\ 0.83 & 0.12 & 0.35 & 0.08 \\ 0.73 & 0.31 & 0.69 & 0.41 \\ 0.72 & 0.49 & 0.72 & 0.23 \end{bmatrix}. \tag{13}$$

(2) According to the data given by the classroom teaching quality index, it can be known that the relative best explanation O_o factor index is

$$O_o = (0.63, 0.48, 0.79, 0.41). \tag{14}$$

(3) Dimensionless processing of indicators (difficulty value, discrimination value, reliability value, and validity value). That is, the matrix is initialized, and the matrix Y is generated as follows:

$$Y = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 0.749 & 0.891 & 0.985 \\ 1.439 & 0.219 & 0.468 & 0.112 \\ 1.171 & 0.631 & 0.831 & 1 \\ 1.273 & 1 & 1 & 0.518 \end{bmatrix}. \tag{15}$$

(4) For the subject of quality of English instruction in the classroom analysis, the weighting vector of the evaluation index can be determined as $\varpi = (1, 1, 1, 1)$

(5) Construct the augmented matrix A' as follows:

$$A' = \begin{bmatrix} 1.063 & 0.672 & 1.026 & 1 \\ 0.534 & 0.373 & 0.458 & 0.369 \\ 0.726 & 1.061 & 1.063 & 0.531 \\ 0.635 & 0.652 & 0.536 & 0.512 \end{bmatrix}. \tag{16}$$

(6) Calculate the comprehensive evaluation value $\psi_i = \sum_{q=1}^{m} \omega_q s_{pq}$. $(\psi_1, \psi_2, \psi_3, \psi_4, \psi_5) = (3.76, 1.753, 3.124, 3.265, 2.316)$. As a result, the quality of English classroom teaching is monitored and evaluated
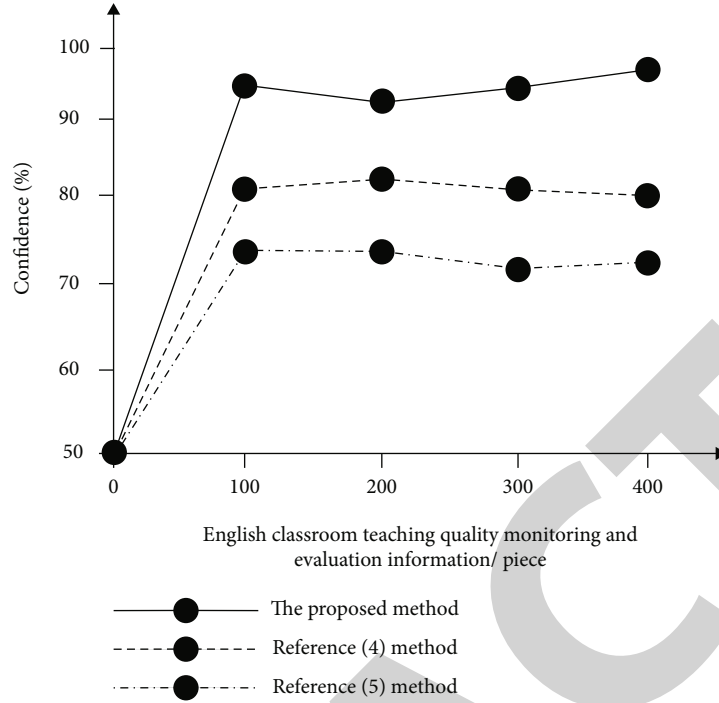
FIGURE 3: Comparison results of reliability of monitoring and evaluation of quality of English instruction in the classroom by different methods.

4. Experimental Analysis

In the experiment section, we will discuss experimental environment and data, quality of English instruction in the classroom monitoring and evaluation reliability, quality of English instruction in the classroom monitoring and assessment accuracy, and monitoring and evaluation time of quality of English instruction in the classroom in detail.

4.1. Experimental Environment and Data. The experiment's hardware environment is an Intel Core i5 1.7 GHz CPU with 4 GB of memory, and the experiment's software environment is a MATLAB simulation platform to test the efficiency of a big data-based monitoring and assessment technique for quality of English instruction in the classroom. Select 50 students from a university as the experimental sample, save student performance information in Oracle database, import data using key fields, select important parts, and import them into SQL Server 2016 database. Use the teaching management system to import the basic information of students and extract the course information from the student management implementation plan. Use Excel software to import students' basic information, strictly control the data format of each field, and clean up the data for the problems such as redundancy and vacancy of original data. In the process of Boolean data mining, association rules are used to manage the data of English classroom teaching performance objects by quantitative means, and discrete interval values are defined. 400 pieces of information data for quality of English instruction in the classroom monitoring and evaluation are derived as a result of the foregoing activities. By comparing the method of reference [4], the method of reference [5],

and the suggested technique, the effectiveness of the proposed approach is demonstrated.

4.2. Quality of English Instruction in the Classroom Monitoring and Evaluation Reliability. The evaluation index for validating the dependability of the suggested approach in quality of English instruction in the classroom monitoring and assessment is the evaluation confidence of the quality of English instruction in the classroom monitoring data. For monitoring and evaluating the quality of English classroom teaching, confidence is the interval estimation of a certain overall parameter of the sample. The higher the level of trust, the more reliable the monitoring and evaluation of the quality of English instruction in the classroom. The following is the calculating formula:

$$\kappa = ZN \left[\frac{2S}{\varphi} \right]^2 \times 100\%. \tag{17}$$

In formula (17), N is the required sample number, Z is the confidence level statistic, S is the total standard deviation, and φ is the confidence interval. The reference method [4], the reference method [5], and the proposed approaches are all compared. Formula (17) is used to determine the reliability comparison results of quality of English instruction in the classroom monitoring and evaluation of different techniques, as illustrated in Figure 3.

According to Figure 3, the average quality of English instruction in the classroom monitoring data evaluation confidence of the method of reference [4] is 81.6 percent, the average quality of English instruction in the classroom monitoring data evaluation confidence of the method of
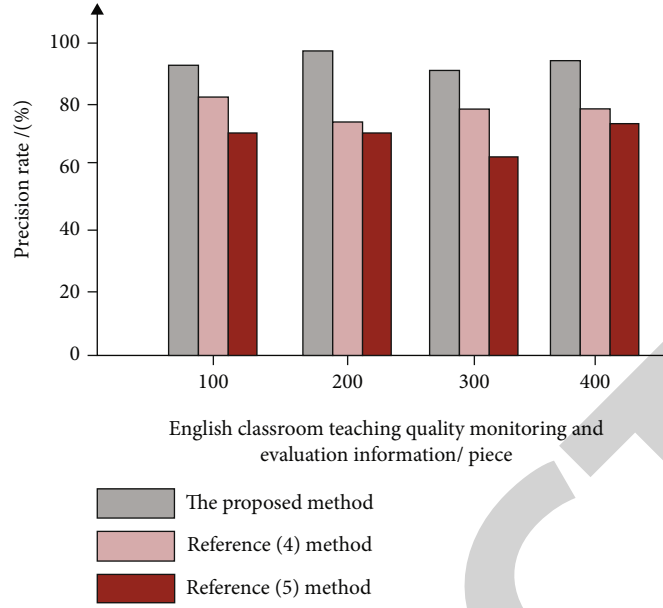
FIGURE 4: Comparison results of different methods of quality of English instruction in the classroom monitoring and evaluation accuracy.

reference [5] is 73.8 percent, and the average quality of English instruction in the classroom monitoring data evaluation. The monitoring data of quality of English instruction in the classroom of the suggested approach has a high level of evaluation confidence, indicating that the monitoring and evaluation reliability of the quality of English instruction in the classroom of the proposed method is good.

4.3. Quality of English Instruction in the Classroom Monitoring and Assessment Accuracy.

The accuracy of the suggested approach in monitoring and assessing the quality of English instruction in the classroom is further validated on this basis, with the evaluation accuracy of quality of English instruction in the classroom monitoring data serving as the evaluation indicator. In the monitoring of English classroom teaching data, the accuracy rate is the ratio of data that confirms the quality of English classroom teaching. The higher the accuracy rate, the more accurate the monitoring and evaluation of the quality of English instruction in the classroom. The formula for the computation is as follows:

$$C_q = \frac{\lambda}{\sigma} \times 100\%. \tag{18}$$

λ is the data that fulfills the quality of English classroom teaching in formula (18) and is the data that is monitored in English classroom teaching. The reference method [4], the reference method [5], and the proposed approaches are all compared. As illustrated in Figure 4, the accuracy comparison results of quality of English instruction in the classroom monitoring and evaluation of different techniques are determined using formula (18)

When 400 pieces of quality of English instruction in the classroom monitoring and evaluation information data are used, the average quality of English instruction in the classroom monitoring data evaluation accuracy rate of the

TABLE 4: Comparison results of monitoring and evaluation time of quality of English instruction in the classroom with different methods.

Quality of English instruction in the classroom monitoring and evaluation information data	The proposed method/s	Reference [4] method/s	Reference [5] method/s
100	7.6	8.9	10.8
200	9.7	13.4	15.4
300	12.5	17.6	20.5
400	15.7	21.8	25.1

method of reference [4] is 80.4 percent, the average quality of English instruction in the classroom monitoring data evaluation accuracy rate of the method of reference [5] is 71.2 percent, and the average quality of English instruction in the classroom monitoring data evaluation accuracy rate of the method of reference [6] is 71.2 percent. It can be shown that the monitoring data of the proposed method's quality of English instruction in the classroom has a high accuracy of evaluation, indicating that the monitoring and evaluation accuracy of the proposed method's quality of English instruction in the classroom is also good.

4.4. Monitoring and Evaluation Time of Quality of English Instruction in the Classroom.

Verify the proposed method's monitoring and evaluation time for the quality of English instruction in the classroom. As indicated in Table 4, compare reference method [4], reference method [5], and the suggested technique, and get the comparison results of quality of English instruction in the classroom monitoring and assessment time of different methods.

Table 4 shows that when the volume of information data for quality of English instruction in the classroom monitoring and evaluation grows, the time spent monitoring and

evaluating quality of English instruction in the classroom with various approaches grows. The quality of English instruction in the classroom monitoring and evaluation time of the method of reference [4] is 21.8 s, the quality of English instruction in the classroom monitoring and evaluation time of the method of reference [5] is 25.1 s, and the quality of English instruction in the classroom monitoring and evaluation time of the proposed method is only 15.7 s when there are 400 pieces of quality of English instruction in the classroom monitoring and evaluation information data. It can be shown that the proposed method's monitoring and evaluation time for quality of English instruction in the classroom is somewhat long.

5. Conclusion and Future Work

The big data-based monitoring and evaluation method for the quality of English instruction in the classroom described in this research fully utilizes the benefits of big data technology. Its quality of English instruction in the classroom monitoring and evaluation has a high level of accuracy and dependability, and it takes a short amount of time to complete. However, in the process of monitoring and evaluating the quality of English classroom teaching, this method merely uses association rules as a starting point for mining the quality of English instruction in the classroom monitoring data, ignoring data analytic techniques such as classification and aggregation. As a result, in the next study, we will use the early warning model to analyze the data to get more precise monitoring and evaluation findings for the quality of English instruction in the classroom.

Data Availability

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

Conflicts of Interest

The author declares that he has no conflict of interest.

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