

# Retraction

# **Retracted: English Teaching Evaluation Model Based on** Association Rule Algorithm and Machine Learning

## Security and Communication Networks

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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

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# WILEY WINDOw

# **Research Article**

# **English Teaching Evaluation Model Based on Association Rule Algorithm and Machine Learning**

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At present, Chinese colleges and universities have a clear understanding of the importance of teaching quality evaluation. They regard the evaluation of teaching quality as an important part of teaching management. This paper aims to study how to analyze and study English teaching evaluation based on association rule algorithm and machine learning and study the model. This paper raises the question of English teaching evaluation. This question is based on modelling studies. So it expounds the concepts and related algorithms of association rule algorithm and machine learning. This paper designs and analyzes a case study of the English teaching evaluation model. The experimental results show that taking a university as the empirical object for specific analysis, according to the evaluation system established in the research, the final score of the questionnaire is 89.2 points, and the English teaching evaluation result is a good grade.

## 1. Introduction

With the fast advancement of the size of advanced education, the nature of instructing has turned into a critical issue. Instructions to successfully and impartially assess the showing nature of school instructors are one of the central points of interest in the examination of universities and instructive organizations lately. Teachers' teaching quality assessment is an effective measure for schools to improve the overall teaching quality. It effectively adapts to teaching behavior, optimizes the structure of teachers, and promotes the improvement of teachers' teaching level and the systematic and scientific management of teachers.

Teachers' teaching quality assessment can create suitable direction and motivation for teachers to improve their own ability, and can promote the improvement of teachers' teaching quality and teaching level, and further develop the quality of education. Along these lines, it is of incredible importance to lead top to bottom and efficient exploration on the current showing assessment model and to make an appropriate showing assessment model on this premise. The innovation of this paper: (1) This paper combines association rule algorithm, machine learning, and English teaching evaluation. It introduces the theory and related methods of machine learning in detail. It mainly introduces decision tree algorithm, random forest, and multiple linear regression. (2) In the face of English teaching evaluation index, it constructs the English teaching evaluation system.

# 2. Related Work

Showing assessment is the judgment of educators' instructing and understudies' learning esteem. It has become an important part of school teaching management and teaching process. Villanueva K A described the practice of teaching assessment in national engineering programs to understand and assess the current state of practice [1]. Wu took the "College English" course as an example to discuss the relationship between blended teaching and ideological and political teaching and analyzed the teaching method of blended teaching. He also put forward suggestions on the reform of the evaluation system in two parts [2]. Zhang

utilized GIS versatile terminal to examine the homeroom showing assessment and direction framework. He made showing more viable through his exploration on instructing assessment [3]. Ruslim explored the relationship between teaching evaluation and lecturer performance [4]. In light of AI, Liu momentarily presented the foundation and current circumstance of instructing assessment. He likewise presented exhaustively the significant calculation standards for information examination and demonstrating utilizing information mining innovation and AI strategies [5]. Myerholtz L explored the existing and desirable characteristics of teacher instructional assessment systems from the perspective of key stakeholders [6]. Liu mainly studied a rule extraction algorithm based on incomplete multiexpert fuzzy language form decision context [7]. Sheng established a theoretical framework for judging the validity of teaching evaluation scores on the basis of item response theory [8]. However, they did not conduct a multifaceted discussion and did not establish a model with practical application significance.

# 3. Methods Based on Association Rule Algorithms and Machine Learning

#### 3.1. Machine Learning

3.1.1. Overview. In the field of machine learning and data mining, classification has always been a very important research direction. The purpose of the classification operation is to generalize and analyze the selected data set to obtain a model or function used in the classification operation. This classification model or function can correspond to a known class label for the sample data to be classified. Both classification and regression algorithms can be used in forecasting research. However, different from the regression algorithm, the output result of the classification method is discrete data, which is the value of the category to which the sample data belongs. The regression method outputs continuous data or ordered values [9, 10].

The core of regression algorithm and classification algorithm is to obtain predicted value based on input value. The difference between the two algorithms is the type of output value. The output of the regression algorithm is a continuous variable, while the output of the classification algorithm is a discrete variable.

*3.1.2. Decision Tree Algorithm.* Decision tree algorithm is one of the most commonly used machine learning algorithms. It is the process of sorting or regressing data through a variety of operating rules [11]. Decision tree can be divided into classification decision tree and regression decision tree classification. Decision trees classify discrete variables and regression decision trees perform regression calculations on continuous variables. An example of a decision tree is shown in Figure 1.

The decision tree algorithm builds a tree, a data structure, to discover possible classification or regression rules in



the data. The core of the decision tree algorithm is to ensure that the constructed decision tree must have the characteristics of high accuracy and small scale. The first is the generation of decision trees: it requires dividing the dataset to be trained into decision trees. The second is the pruning of the decision tree: it uses the pruning technology to detect the decision tree generated in the previous step. This is mainly to use the validation set to test the classification and regression rules of the decision tree and remove those branches that affect the accuracy [12, 13].

The steps of the decision tree algorithm are as follows:

- (1) It starts with a single node of the training set.
- (2) If the attributes all belong to a set, it marks the tree node to be a leaf.
- (3) Otherwise, the algorithm will select the attribute with the most powerful classification ability as the current node of the tree.
- (4) The training will be divided into many subsets according to the difference of the attribute values of the nodes currently to be divided, and each attribute value is divided into a branch. It recursively executes the previous steps to construct a decision tree for the subsets obtained by the previous steps.
- (5) It stops the classification step when one of the following conditions is met: all samples to be trained are classified into the same class. All properties are already used when dividing the samples. If a branch does not contain already classified samples, then it divide the larger number of samples into a leaf.

Because the C4.5 algorithm has the ability to perform calculations on continuous variables, the C4.5 algorithm is used when selecting attributes. When selecting attributes for division, the C4.5 algorithm uses the information gain rate for consideration. This avoids the selection defect of attributes with many values when using information gain. The information gain rate is defined as follows:

$$GainRatio(Z) = \frac{Gain(Z)}{SplitInfo(Z)}.$$
 (1)

Gain(Z) is the information gain, and its formula is as follows:

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$$Gain(Z) = Info(Q) - Info_Z(Q).$$
 (2)

And SplitInfo(Z) is the split information value, and its formula is as follows:

$$SplitInf(Q) = -\sum_{b=1}^{u} \frac{|Z_B|}{|Z|} \times \log_2\left(\frac{|Z_B|}{|Z|}\right).$$
(3)

Decision tree algorithm has the advantages of high classification accuracy, simple generation algorithm, antinoise data, and good robustness. It has been extensively studied and explored by researchers in the field of machine learning.

3.1.3. Random Forest. Random Forest is a machine learning method developed by a professor at the University of California, Los Angeles in 1995. Random forest is a modern machine learning technique. It has both classification and regression functions and can also perform autonomous learning [14].

Random forest is a basic learner with a decision tree as the bottom layer, and then a method of selecting random attributes is added when training the decision tree, and finally, these basic learners are built using Bagging ensemble. The process framework of random forest is shown in Figure 2, and the algorithm steps are as follows:

- (1) It uses a sampling technique to select *m* data from the training set.
- (2) It selects z attributes using random attribute selection technique and then selects an optimal node to build a decision tree. z is generally  $\log_2 p$ , and p represents the total number of attributes.
- (3) It repeats the above two steps n times to create n decision trees.
- (4) These n decision trees form a random forest.
- (5) It obtains the final output result through voting method.

3.1.4. Multiple Linear Regression. The multiple linear regression model is one of the commonly used algorithms for solving regression problems.

The univariate linear regression model is suitable for use when only one variable has a large effect on the outcome. In practical regression problems, the results are rarely affected by a single variable, so multiple linear regression works well in practice [15].

Assuming that there is a linear relationship between the target variable Y and multiple variables  $X_1, X_2, ..., X_j$ , the relationship between Y and  $X_1, X_2, ..., X_j$  can be calculated by a linear function, which is called a multiple linear regression model. Its formula system form is as follows:

$$Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \dots + \alpha_j X_j + \eta.$$
(4)

Y is the target variable,  $X_1$ ,  $X_2$ , ...,  $X_j$  are *j* variables,  $\alpha_b$  (b = 0, 1, 2, ..., j) is the *j* + 1 parameters to be solved, and  $\eta$  is the random error term.

The linear formula between the expected value of the target variable Y and the variables  $X_1$ ,  $X_2$ , ...,  $X_j$  is the overall regression formula. Its formula system form is as follows:

$$E(Y) = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \dots + \alpha_j X_j.$$
 (5)

For *m* groups of observations  $X_{1a}$ ,  $X_{2a}$ , ...,  $X_{jb}$ ,  $Y_a(1, 2, ..., m)$ , the formula is in the following form:

$$Y_a = \alpha_0 + \alpha_1 X_{1a} + \alpha_2 X_{2a} + \dots + \alpha_j X_{ja} + \eta_a, (a = 1, 2, \dots, m).$$
(6)

Its matrix form is as follows:

$$\begin{bmatrix} Y_{1} \\ Y_{2} \\ \cdots \\ Y_{a} \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ X_{11} \\ X_{12} \\ \cdots \\ X_{1m} \\ X_{21} \\ X_{22} \\ \cdots \\ X_{2m} \\ \cdots \\ X_{2m} \\ \cdots \\ X_{jn} \end{bmatrix} + \begin{bmatrix} \eta_{1} \\ \eta_{2} \\ \cdots \\ \eta_{m} \end{bmatrix},$$
(7)

where  $Y_a$  is the observation matrix vector of Y,  $X_{jm}$  is the observation matrix vector of variables  $X_1, X_2, ..., X_j$ ,  $\alpha_j$  is the regression coefficient matrix vector, and  $\eta_m$  is the random error term matrix vector.

The multiple linear regression model contains multiple variables, and multiple variables act on the target variable Y at the same time. If it wants to evaluate the influence of one of the variables on the target variable Y, it must be stipulated that the quantitative analysis and calculation should be carried out under the condition that the other variables remain unchanged. Therefore, the regression coefficients in the model are partial regression coefficients. It can also be said that when other variables are fixed, the influence of one of the variables on the target variable Y can be viewed.

Since parameters  $\alpha_B (b = 0, 1, 2, ..., j)$  are all unknown,  $X_{1a}, X_{2a}, ..., X_{j\tau}, Y_a(1, 2, ..., m)$  can be used to estimate

vote

FIGURE 2: Random forest process frame diagram.

Tree

Classifier 1

Tree

Classifier 2

Tree

Classifier 3

X

Automatic

sample set 1

Automatic

sample set 2

Automatic

sample set 3

them. Assuming that after the calculation, the obtained parameter estimate can be expressed as  $\hat{\alpha}_B(b = 0, 1, 2, ..., j)$ , then the parameter  $\hat{\alpha}_B(b=0,1,2,\ldots,j)$  in the above regression formula can be replaced by  $\alpha_B (b = 0, 1, 2, ..., j)$ , then the multiple linear sample regression formula is as follows:

All training

samples

$$\widehat{Y}_a = \widehat{\alpha}_0 + \widehat{\alpha}_1 X_{1a} + \widehat{\alpha}_2 X_{2a} + \ldots + \widehat{\alpha}_j X_{jm}, \tag{8}$$

where  $\hat{\alpha}_{b}$  (*b* = 0, 1, 2, ..., *j*) is the parameter estimate, while  $Y_B(b=0,1,2,\ldots,j)$  is the sample regression value of  $Y_a$ .

Residual  $e_{\tau}$  is the difference between the estimate of the target variable obtained from the multiple linear sample regression formula and the true value Y, The system of equations for residual  $e_{\tau}$  is defined as follows:

$$e_{\tau} = Y_a - \widehat{Y}_a = Y_a - \left(\widehat{\alpha}_0 + \widehat{\alpha}_1 X_{1a} + \widehat{\alpha}_2 X_{2a} + \ldots + \widehat{\alpha}_j X_{jm}\right).$$
(9)

The multiple linear regression model has the following advantages:

- (1) The model can be constructed simply and conveniently
- (2) If the data are determined, the calculation result of the model is unique
- (3) The model can quantitatively evaluate the degree of correlation between each variable

3.1.5. Naive Bayes Algorithm. Naive Bayes algorithm is a very representative machine learning classification algorithm, and it is also a classic classification method based on probability theory. Naive Bayes has the characteristics of simple and easy-to-understand principles and easy implementation. Therefore, the Naive Bayes algorithm is applied in many fields [16, 17]. In the Naive Bayes algorithm, it is considered that each feature attribute is independent of each other, and there is no interdependent relationship.

Structure diagram of the Naive Bayesian model is shown in Figure 3.

For a given training data set, it first assumes that each feature attribute is independent of each other and learns the



joint probability of input data and output class. It then uses Bayes' theorem to calculate its posterior probability based on the sample to be classified by this model. The category value corresponding to the maximum posterior probability is the final classification result of the sample to be classified. Assuming that the feature attributes are independent of each other, the posterior probability is as follows:

$$P(d|s) = \frac{P(d)P(s|d)}{P(s)} = \frac{P(d)}{P(s)} \prod_{a=1}^{m} P(s_a|d).$$
(10)

The formula of Naive Bayesian classification is as follows:

$$h(s) = \arg\max P(d) \prod_{a=1}^{m} P(s_a|d).$$
(11)

Preparing a guileless Bayes classifier is to involve the information in the preparation dataset to compute the earlier likelihood of each class and the restrictive likelihood of each quality. The formula for working out the earlier likelihood of a class is as per the following:

$$P(d) = \frac{|C_d|}{|C|}.$$
(12)



random

forest

In the formula,  $|C_d|$  represents the total number of samples whose class label is d in the training data set C, and |C| is the total number of samples in the training data set.

The calculation of conditional probability depends on the type of data. If the data of the feature attributes are discrete values, the conditional probability is the ratio of the a-th feature attribute value of the class label *d* in the training data set to the total number  $s_a$  of samples  $|C_{d,s_a}|$  to the number of samples  $|C_d|$  of the class label *d*. The formula is as follows:

$$P(s_a|d) = \frac{\left|C_{d,s_a}\right|}{\left|C_d\right|}.$$
(13)

If the feature attribute is continuous data, according to the probability density function, it is assumed that the conditional probability obeys the normal distribution:

$$P(s_a|d) = \frac{1}{\sqrt{2\pi\delta_{d,a}}} \exp\left(-\frac{\left(s_a - \vartheta_{d,a}\right)^2}{2\delta_{d,a}^2}\right),\tag{14}$$

where  $\vartheta_{d,a}$  is the mean on the *a*-th feature attribute in category *d* and  $\delta_{d,a}^2$  is the variance on the *a*-th feature attribute in category *d*.

#### 3.2. Data Mining

3.2.1. Concept. Data mining (DM for short) is simply to mine or extract knowledge from a large amount of data [18]. Data mining is also known as knowledge discovery from database (KDD for short). It is a complex process of extracting and mining unknown and valuable patterns or laws from a large amount of data. The process is shown in Figure 4.

As should be visible from Figure 4, the whole information mining process incorporates various mining stages. What's more, information mining is only one of the primary advances. Although information mining is only an important stage in the whole information mining process, but the expression is just a significant stage in the entire information mining process. However, the expression "information mining" has been broadly utilized and for the most part acknowledged in the fields of industry, media, and data set research. Data mining is the discovery of interesting knowledge from large amounts of data in databases, data warehouses, or other information repositories.

3.2.2. Classification Algorithm: Support Vector Machine. The SVM can correctly classify all training samples such that the points in the training samples are closer to the grading surface to the longest distance from the grading surface. Solving the optimal separating hyperplane is the basis of the support vector machine, which enables the training data to be divided correctly and the geometric spacing is maximized. For linearly separable datasets, the basic idea and formalized convex quadratic programming problem are as follows:  $\max_{wb} \chi$ 

$$s.t. y_i \left( \frac{w}{\|w\|} \cdot x_i + \frac{b}{\|w\|} \right) \ge \chi, i = 1, 2, \dots N,$$

where  $\chi_i = y_i((w/||w||) \cdot x_i + (b/||w||))$  defines the geometric space of the hyperplane relative to the sampling point  $(x_i, y_i)$ , and  $\chi = \min_{i=1,2,..,N} \chi_i$  is the minimum value of the geo-

metric space of the hyperplane at all sampling points.

$$\min_{\alpha} \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) - \sum_{i=1}^{N} \alpha_i$$

$$s.t. \sum_{i=1}^{N} \alpha_i y_i = 0 (0 \le \alpha_i \le C, i = 1, 2, \dots N).$$
(16)

Among them, the penalty parameter C > 0, and the most *E* solution is  $\alpha^* = (\alpha_1^*, \alpha_2^*, \dots, \alpha_N^*)^T$ .

For nonlinear classification, the interinstance inner product can be turned into a kernel function. For x, k in any input space, we have the following equation:

$$Z(x,k) = \varphi(x) \cdot \varphi(k), \qquad (17)$$

Support vector machines have been widely used in neuroscience and bioinformatics because the algorithm can handle high-dimensional data well. Its main disadvantage is the large amount of calculation and easy overfitting.

#### 3.3. Association Rule Algorithm

*3.3.1. Introduction.* One of the most widely used methods in data mining is association rules. It mainly studies the problem of what implies what. Here are some basic concepts.

(1) Items and itemsets: each field in the data table has a different value, and each value is an item. A set of objects is described as a set of elements, while a set of k objects is represented as a set of k elements.

It sets item set  $A = \{A_1, A_2, A_3, \dots, A_l\}$  because the itemset contains *l* items, so is called an l-itemset, such as {English, mathematics} is a 2-item set.

(2) Transaction: transactions are a subset on itemset A, i.e.,  $W \subseteq A$ . It is represented by the identifier WAS, and the database transaction set is composed of transactions, represented by S.

(3) Support number and support: the support count is the number of times the itemset X appears in the transactional database, represented by  $\phi_x$ . Support (support) is the ratio of the support number of the itemset to the total number of transactions in the transaction database, which can be represented by X.sup or supprt(X). The calculation of support is shown in the following formula:

$$\sup port(X) = \frac{\phi_X}{|S|},\tag{18}$$

where |*S*| represents the total number of transaction database transactions.



FIGURE 4: Schematic description of the whole process of knowledge mining.

Minimum user-defined support can be represented by min\_sup.

(4) Confidence: confidence is a feature of association rules. The trust degree of association rule  $X \Rightarrow Y$  describes that a transaction in the transaction database contains both X and Y and can be represented by  $conf(X \Rightarrow Y)$ . Its calculation method is shown in the following formula:

$$conf(X \Rightarrow Y) = \frac{\sup port(X \cup Y)}{\sup port(X)},$$
 (19)

Likewise, the minimum confidence level is set by the user and can be represented by min\_conf.

(5) Frequent itemsets: if an itemset X has a relationship:  $\phi_x \ge \min x\_\sup * |S|$  or  $\sup port(X) \ge \min x\_\sup$ , then X is called a frequent itemset or a large itemset. The core work of mining association rules is to find frequent itemsets.

(6) Association rules: an association rule is an implication  $X \Rightarrow Y$  of the form, where  $X \subseteq A$  and  $Y \subseteq A$ , it is used to describe the implicit relationship that exists between the data items in the transaction database. X is its predecessor and Y is its successor.

Its support degree support  $(X \longrightarrow Y)$  is greater than or equal to the specified minimum support degree min\_sup, that is, the transaction number of support  $(X \longrightarrow Y) * |S|$ in the transaction database contains both X and Y.

Its confidence level of  $conf(X \Rightarrow Y)$  is greater than or equal to the set minimum confidence level min\_conf, that is, there is a possibility of  $conf(X \Rightarrow Y)$  that the transaction in the transaction database contains Y when it contains X.

*3.3.2. Excavation Process.* The main work of association rules includes the following two aspects:

 It finds frequent itemsets: it finds itemsets whose help degree is more noteworthy than or equivalent to the base set by the client. For rules that require constraint semantics, it looks for itemsets that conform to the specification.

(2) Generating association rules: the association rules are generated from the frequent itemsets found in step 1, and the confidence of these association rules is not less than the minimum confidence given by the user. If there is a frequent item set *L*, it is necessary to check each nonempty subset *X* of *L* in turn, generate an association rule x = L - X, and obtain the confidence level of the association rule. It retains the association rules whose confidence is not less than the minimum confidence and discards the rest. According to the nature of association rules, this step can be simplified to first check the largest subset of *L* as the antecedents of the rule. It is only necessary to test smaller subsets when the conditions are met [19].

Because the process of generating association rules no longer scans the transaction database, the first step in the mining process is to discover frequent itemsets.

The whole process of mining association rules can be simplified as shown in Figure 5.

3.3.3. Classification. Association rules are the first problem involved in data mining, and it is also a major trend in the development trend of data mining. In the early days, data mining was primarily concerned with defining and designing algorithms for relevant rules. As more and more researchers join in the study of association rules, there are thousands of association rules papers in various forms, showing a state of blooming. According to the different dimensions of the connection rules, they are divided into the following types (Figure 6).



FIGURE 6: Classification of association rules.

# 4. Experiment and Analysis of the English Teaching Evaluation Model

4.1. Constructing the English Teaching Evaluation System. According to the requirements of the "National College English Curriculum Guidance Outline", China aims to strengthen the educational evaluation concept of continuous improvement between teachers and students. It applies modern sociology, pedagogy, and other theories [20], starting from various conditions and related aspects of English teaching, as shown in Figure 7(a).

Physical education in colleges and universities is an important part of education. Its teaching quality directly reflects the school's teaching level and even affects the reform of the entire educational process. The index content of the evaluation system is mainly composed of five indicators: lesson preparation, teaching content, teaching attitude, teaching effect, and teaching organization (Figure 7(b)).

The hierarchical structure model of English teaching evaluation is divided into three-level indicators, including one level-1 indicator, five level-2 indicators, and 20 level-2 indicators. The first level index is the target level, that is, the comprehensive evaluation of English teaching. The second level index is the main factor layer, including lesson preparation, teaching content, teaching organization, teaching attitude, and teaching effect. The third level indicator is the secondary factor layer. It includes reasonable preparation of teaching plans, reasonable design of teaching methods, adequate preparation of venue equipment, sufficient understanding of students' situation in teaching, active teaching in classroom atmosphere, reasonable progress of physical education courses, large amount of teaching content, accurate teaching content, passwords, movements, novel teaching content, reasonable use of venue equipment, the continuity of the teaching process is strong, the course progress is reasonable, the teachers are proficient in basic teaching skills, get out of class is on time, the students are the main body, the communication between teachers and students in the classroom is good, the students have mastered the sports skills they have learned, the content is interesting, the students' physical and mental exercise are exercised, and the students' interest in sports learning is improved.

It uses the collective survey method to determine the importance of each indicator for five 2-level indicators. It divides the importance of each indicator into five levels (5 points for very important, 4 points for more important, 3 points for general, 2 points for not very important, and 1 point for very unimportant): very important, relatively important, general, not very important, and very unimportant, respectively. It judges the importance of each index in the evaluation system according to the scores of 10 experts. A ratio below 0.70 indicates that the indicator is not very important. The judgment results are shown in Tables 1 and 2.

Finally, an English teaching evaluation index system including twenty 3-level indicators and five 2-level indicators was constructed through the screening of level 2 and level 3 indicators; they are shown in Table 3.

4.2. Demonstration of the English Evaluation System in a University. The questionnaires for leaders or teachers and students in this paper are designed according to the three-level indicators in the evaluation index system. The issues



FIGURE 7: English teaching evaluation system. (a) Principles of establishing English teaching evaluation indicators. (b) Contents involved in the English teaching evaluation system.

TABLE 1:	Experts'	views on th	e importance	of sec	ondary	indicators	of Eng	glish t	eaching	evaluation

Secondary indicators	Relative importance					Total	Eull acore	Patio	
secondary indicators	5	4	3	2		1	Iotai	Full score	Katio
Preparation for lessons	7	2	1				46	50	0.92
Teaching content	8	2					48	50	0.96
Teaching organization	9	1					49	50	0.98
Teaching attitude	7	2	1				46	50	0.92
Teaching effect	9	1					49	50	0.98

TABLE 2: Experts' views on the importance of the three-level indicators of English teaching evaluation.

Three-level indicator		Relative importance					Eull seens	Datio
		4	3	2	1	Total	Full score	Katio
Reasonable writing of lesson plans C11	3	5	2			41	50	0.82
Reasonable design of teaching methods C12	5	1	4			41	50	0.82
Textbook resources are well prepared C13	4	3	3			41	50	0.82
Fully understand the situation of students in teaching C14	5	2	2	1		41	50	0.82
Interesting teaching content C21	5	1	4			41	50	0.82
English course progress is reasonable C22	8	1	1			47	50	0.94
The teaching content has a large amount of information C23	7	3				47	50	0.94
Correct teaching content C24	5	4	1			44	50	0.88
Novel teaching content C25	3	5	2			41	50	0.82
Teachers are proficient in basic teaching skills C31	5	2	2	1		41	50	0.82
Be on time for class and end of get out of class C32	2	3	2	3		34	50	0.68
Active classroom atmosphere C33	4	3	3			41	50	0.82
Student-centered C34	6	2	2			44	50	0.88
Good communication between teachers and students in the classroom C41	6	4				46	50	0.92
Students master the English knowledge they have learned C42	8	2				48	50	0.96
Students' English ability is improved C43	7	3				47	50	0.94
Students' interest in English learning increases C44	10					50	50	1.0
Reasonable use of teaching materials C51	6	2	2			44	50	0.88
Strong continuity of teaching process C52		1				49	50	0.98
Scientific rigorous C53	9	1				49	50	0.98

involved are classified and transformed accordingly according to the subject of the evaluation. It finally forms two related questionnaires for leaders (i.e., teachers) and students, respectively. It uses the established English teaching evaluation model, compares it according to the unified Saatyl-9 judgment matrix standard scale, and constructs six judgment matrixes. The weight of English teaching evaluation

	Secondary indicators	Three-level indicator						
		Reasonable writing of lesson plans C11						
	Duranting for large P	Reasonable design of teaching methods C12						
	Preparation for lessons B1	Textbook resources are well prepared C13						
		Fully understand the situation of students in teaching C14						
		English course progress is reasonable C22						
		The teaching content has a large amount of information C23						
	Teaching content B2	Correct teaching content C24						
	6	Novel teaching content C25 Interesting teaching content C21						
English teaching evaluation		Student-centered C34						
system	Traching and significant D2	Active classroom atmosphere C33						
	leacning organization B3	Teachers are proficient in basic teaching skills C31						
		Be on time for class and end of get out of class C32						
		Students' interest in English learning increases C44						
		Students master the English knowledge they have learned C42						
	Teaching attitude B4	Students' English ability is improved C43						
	C C	Good communication between teachers and students in the classroom						
		C41						
		Strong continuity of teaching process C52						
	Teaching effect B5	Scientific rigorous C53						
	0	Reasonable use of teaching materials C51						
		0						

TABLE 3: English teaching evaluation structure model.

TABLE 4: B1, B2, B3, B4, and B5 judgment rectangle matrix for A.



FIGURE 8: Comparison of indicator weights. (a) Comparison. (b) Weight value comparison.

index adopts "Delphi method." It invited 10 experts in the field of English teaching. After three rounds of expert questionnaires, it finally calculated the indicator weights. This paper takes the calculation method of *B*1, *B*2, *B*3, *B*4, and *B*5 for the judgment rectangular matrix of A as an example (Table 4).

The index weights are calculated according to Table 4, and the comparison is shown in Figure 8(a). It calculates the weights of the remaining five rectangular matrices, and the weight value comparison is shown in Figure 8(b).

A random questionnaire survey was conducted among 231 students. Among them, 121 girls and 110 boys were all



FIGURE 9: Questionnaire data graph. (a) Questionnaire recovery. (b) Calculation of the score coefficient.

valid questionnaires, and the questionnaire recovery rate was 100%. The survey statistics are shown in Figure 9(a).

It divides the average score of the questionnaire in the statistical situation table by five (because there are 5 secondary indicators). The obtained value is multiplied by the corresponding total weight value and multiplied by 100% to obtain a final score of 89.2 points. The student's questionnaire results rated the teacher as good. The final score is more scientific and more reasonable than the primary score, as shown in Figure 9(b).

#### 5. Discussion

This paper analyzed how to conduct research on English teaching evaluation based on association rule algorithms and machine learning. This paper expounds the association rule algorithm and machine learning concepts and algorithms; studies machine learning; and explores data mining. It also analyzes the applicability of association rule algorithm and machine learning in teaching evaluation through experiments.

There are many common teaching evaluation systems, most of which evaluate the behavior of teachers, while the learning process and effects of students are rarely mentioned. Simultaneously, the work process of carrying out showing assessment is bulky, and it frequently needs to finish an enormous number of information estimation undertakings. Subsequently, how to utilize present-day science and innovation to lay out a total, objective, and feasible classroom teaching evaluation system and optimize the evaluation process is an important problem that needs to be solved urgently.

Based on the principle of English teaching evaluation, it uses the Delphi method to collect indicators through expert questionnaires to determine the English teaching evaluation model. It calculates the weight coefficient of the index according to the calculation index weight coefficient and establishes a matrix of relative importance one by one in combination with the implementation status of the English teaching evaluation by experts. It has a certain scientific basis, thus avoiding the artificial subjective intentionality of the evaluation in most studies.

### 6. Conclusion

Information investigation is indivisible from information mining, which is a progression of examination and handling of information. The information is examined in mining structure on the guideline of affiliation rules. The use of related information has gotten broad consideration, so how to work on the functional proficiency of affiliation rules has generally been the focal point of exploration. The utilization of information mining innovation in the field of schooling has not been read up for quite a while. As individuals focus on this innovation, it is accepted that its execution in the field of instruction will turn out to be increasingly broad, and it will assume a gigantic part in advancing schooling change and advancement.

#### **Data Availability**

No data were used to support this study.

### **Conflicts of Interest**

The authors declare that there are no conflicts of interest regarding the publication of this article.

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