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Research Article

Quality Evaluation of Student Education Management Work Based on Wireless Network Data Mining

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Higher education has a major role to play in social progress, technology, and economic development. However, as the number of students enrolled in higher education increases, the quality of graduates is declining and their ability to work is being questioned. Therefore, it is very important to effectively evaluate the quality of teaching and learning. With this in mind, an evaluation approach using data mining based on wireless networks is proposed in this paper. In the educational work of universities, data mining helps to assist universities to improve management efficiency and teaching effectiveness in managing students by mining and analyzing large-scale educational data. In order to improve their teaching management, this paper uses the Apriori method among correlation rule mining methods. The algorithm is improved in terms of time efficiency, and then the improved algorithm is used to mine and analyze the impact of teachers' age, title, educational background, and student performance on teaching quality evaluation. The results of the exploration showed that, through the mining algorithm, it was found that the student's evaluation was proportional to the student's performance. For example, the average grade was excellent, and most evaluation grades were excellent. Its support level was 26% and its confidence level was 62.5%, indicating that more than half of the students met its characteristics. It also showed that the results were real, and the quality of teachers' teaching could be known through the results of students.

1. Introduction

At present, the informatization of colleges and universities is developing very rapidly. As for the current situation, all colleges and universities across the country have established their own campus networks. In the context of the rapid development of wireless networks, how to successfully apply information technology to university education in order to improve the utilization rate of resources has become a hot topic. For example, the university has improved the teaching management system, greatly improving the day-to-day management of university administrators and helping them manage the daily and learning behavior of students. Universities are densely populated areas. Their management systems accumulate vast amounts of data and information. The state's support for university education has not only expanded the number of enrolments, but also improved the educational work of various universities, which has brought new requirements and challenges to the teaching and teaching methods of schools. It will be very meaningful and valuable to use existing resources and technologies in order to discover the rules behind some educational data and information and use these discovered rules to improve the quality of teaching and learning.

As an interdisciplinary technology, data mining technology involves many disciplines, including high-performance computing, pattern recognition, databases, inductive reasoning, and other fields. In recent years, the application of data mining technology in higher education has attracted people's attention, for example, predicting college enrolment, predicting students' graduation status, investigating students' learning experience, and assisting students in choosing courses. After years of development, data mining technology has received extensive attention from relevant researchers in the industry. The progress and popularization of computer and network technology has laid a solid foundation for the development of data mining technology. Data mining has established its own discipline by absorbing theoretical research results and practical research results in various fields. So far, the achievements of data mining have led to the development of data mining technology in both theoretical and applied research fields. There are good prospects for development.

In terms of teaching quality assessment, this paper takes association rules in data mining technology as the technical point of student evaluation analysis and discovers the relationship between student evaluation and teaching quality through association rule algorithm. Through the law of this connection, which can help teachers to formulate teaching plans, the quality of teaching can be improved. In addition, the Apriori algorithm applied in this paper has low time efficiency and information accuracy due to frequent access to the database and the redundancy of the rules generated by support confidence. Based on this, the Apriori algorithm of the application is improved to improve the time efficiency.

1.1. Related Work. With the spread of education and economic development, the quality of teaching and learning in higher education has become an issue of social concern. Researchers around the world have been studying the relevant influencing factors, and Yeo has proposed a student-monitoring-based course quality management with an emphasis on narrative evaluation to help identify the course's strengths as well as strengths and improve the quality of the course by collecting quality messages from students' perspectives [1]. Using evaluation characteristics commonly used by university faculty, Kim investigated aspects of the dimensions of companion evaluation standards used in advertising management and physical education courses by college students. Overall, students were more likely to use quality of work than team work when evaluating team peers [2]. Gjurchinovski took evaluation as an integral part of the course process and had an important position as the end and starting point in the educational process. The concept of evaluation in the educational process could be used to evaluate educational programs and their quality. During the assessment process, fundamental areas of the entire educational process were always considered. Accordingly, it was safe to argue that evaluation was inherent in the work of education [3]. Zimmermann et al. examined ways to design an effective, fair, and continuously improving admissions process systematically, condensing and analyzing a large amount of data from student records to identify ways to obtain high-value feedback. Both undergraduate grades and GRE General Test scores were evaluated and both were found to be effective admissions tools in a European context [4]. Different countries in the world have different educational systems and different systems of student formation, which is one of the factors that influence the quality of student development. Diasamidze et al. believe that the quality of higher education must take into account the characteristics of the university. Moreover, the qualitative evaluation system is an integrated system of quantitative and qualitative characteristics used to diagnose the effectiveness of an educational system [5]. Zhang analyzed the concept and value orientation of the quality management system of college education from the establishment of the quality management system as well as the improvement of the service process. He also constructed a quality management system of college education based on big data [6]. Rodrigues et al. presented a retrospective review of EDM research in the teaching and learning process from an educational perspective, which had never been explored before. The articles which were analyzed show that EDM research has expanded into several areas and topics, including pedagogical research on interactions between educational participants, monitoring and evaluation of the teaching and learning process, evaluation of pedagogical actions taken by administrators, learning risks, and educational media recommendations and recovery [7]. These studies have focused on the topic of the lack of relevance to the use of the Internet when conducting a comprehensive analysis of educational quality assessment systems. This paper builds on their work by using data mining algorithms to further assess the quality of teachers' instruction based on wireless network penetration. The relevant applications of the data mining algorithm are collected below.

Data mining has played an active role in modern information technology. Scholars around the world have explored its applications. To improve efficiency, sensor samples collected by sensor nodes are mined for spatial and temporal data. Kumar and Chaurasiya proposed a strategy to eliminate redundancy by mining the gathered data to select appropriate information and then relaying it to the base station or cluster head in the wireless sensor network, thus eliminating redundancy [8]. Chen investigated BP neural network-based classifier models, combinations of BP neural network models, and other optimization algorithms, ultimately demonstrating that the use of an improved Adaboost_BP classifier can improve the efficiency of hotel management by at least 75% [9]. With the development of higher education in our country, many new problems and challenges have emerged in the teaching and management of colleges and universities. Huizhen expounded the data mining technology, used the improved Apriority algorithm, established a teaching quality evaluation model, analyzed various information of students and teachers, and obtained more accurate teaching quality evaluation results [10]. In order to optimize the management process of cold chain logistics and improve management efficiency, He and Yin used mathematical calculations based on neural network algorithm and grayscale prediction, and R program 4.0.2 used data from 2013 to 2019 to build two prediction models to explore the cold chain logistics demand [11]. The research focused on the application of mining algorithms, but most of them were used in economic commercialization, and the research results that applied them to teaching quality evaluation were relatively rare.

2. Teaching Quality Assessment Methods

In the context of the popularization of wireless network in campus, this paper establishes a teaching quality evaluation system by combining data mining method with it and evaluates the quality of education work from the perspective of student evaluation. The data mining method used in this paper is described in detail.

2.1. Data Mining System

2.1.1. Data Mining System. The primary inputs to the data mining system are commands entered by the user through the graphical interface, data from the data warehouse, and knowledge stored in the repository of the database of the data marketing solution [12]. During the data mining tool, the data selected from the data warehouse is fed to several mining algorithms to discover patterns in the data and relational knowledge. Some knowledge is also added to the knowledge base for subsequent discovery extraction as well as assessment [13]. The structure of a typical data mining is shown in Figure 1.

2.1.2. Data Mining Environment. The data extraction is a complete procedure to find formerly unknowable, effective, operational information in large datasets as well as to use this information for decision making and knowledge enrichment. The environment for data mining is shown in Figure 2.

2.1.3. Basic Concepts and Theories of Data Mining. Data mining has a short history, but it has grown rapidly since the 1990s. Moreover, it is a product of interdisciplinary synthesis. There is not yet a complete definition. The definition commonly used today is described as knowledge discovery in databases, or KDD for short. It is the sophisticated procedure of mining and extracting known and valuable patterns or regularities out of large amounts of data. Data exploration can be divided into three main phases: data preparation, data mining, and representation and interpretation of results. The expression and interpretation of results can also be subdivided into evaluation, interpretation of model models, consolidation, and application of knowledge. Knowledge discovery in database is also a multistage process, and the three stages are executed iteratively, as shown in Figure 3.

2.1.4. Data Mining Features. Data mining generally has two functions—namely, prediction verification function and description function. Prediction verification refers to other unknown attribute values predicted or confirmed by some known data base, while findings of description function can be used to describe data and understand patterns [14]. Figure 4 shows the main functions of numerology mining.

According to the goal of data mining, in the process of knowledge discovery, a variety of mining methods are often used to obtain the desired knowledge. Common data analysis methods include classification analysis, cluster analysis, association analysis, outlier analysis, regression analysis, sequential pattern mining, and visual pattern mining [15].

2.1.5. Classification Analysis. Classification analysis is a model that distinguishes different object types. By predefining the category of the target, the category to which the classified object belongs is determined. This is a supervised pattern recognition method. It analyzes the data of a predefined category database, accurately describes and models each category, obtains a reasonable classification model or rule, and then uses the classification model in order to analyze unclassified data to determine the type of object. Categorical analysis can be used not only to classify data, but also to predict. This method has been widely used in risk analysis, biological science, user behavior analysis, and so on. For example, banks use it to classify credit card users as good, fair, and poor.

2.1.6. Cluster Analysis. Clustering is to divide each record into various categories, so that the difference between each category is as large as possible, and the difference between objects in the same category is as small as possible. Clustering originates from classification, but unlike classification, clustering is not clear about the class to be divided into before starting the analysis. There are many methods of cluster analysis, including systematic clustering, fuzzy clustering, and so on. These methods may also produce different results for cluster analysis of the same dataset. So far, many scholars have applied clustering algorithms to behavior analysis.

2.1.7. Association Analysis. Association analysis is to find a certain relationship between objects in huge data. This association that frequently appears in big data is an association rule. In association analysis, by analyzing the internal relationship between data transactions and their states and trends, frequently occurring association rules are found, which are generally the probability of an event occurring. The research of this paper is mainly to explore the relevance of teaching quality through association rules. The following introduces several basic concepts of the association algorithm.

As the most widely used association rule in data mining, association analysis, like cluster analysis, belongs to an unsupervised learning method, which is mainly used to discover the interdependence between the features of different objects.

Items and itemsets: Different fields in the data table have different values. Each single value is an item. Itemset is a collection of items, and the F-item represents a collection containing F items.

Transaction: A subset of the itemset is the transaction, and in the transaction with the identifier Tid, the transaction set of the database is composed of transactions. It is denoted here as W.

Support number and support degree: The support number is the number of times the itemset F appears in the transactional database. The support degree is the ratio of the support number ϕi in the item set to the total number of transactions in the transaction database, indicating the frequency of cooccurrence of antecedents and consequent

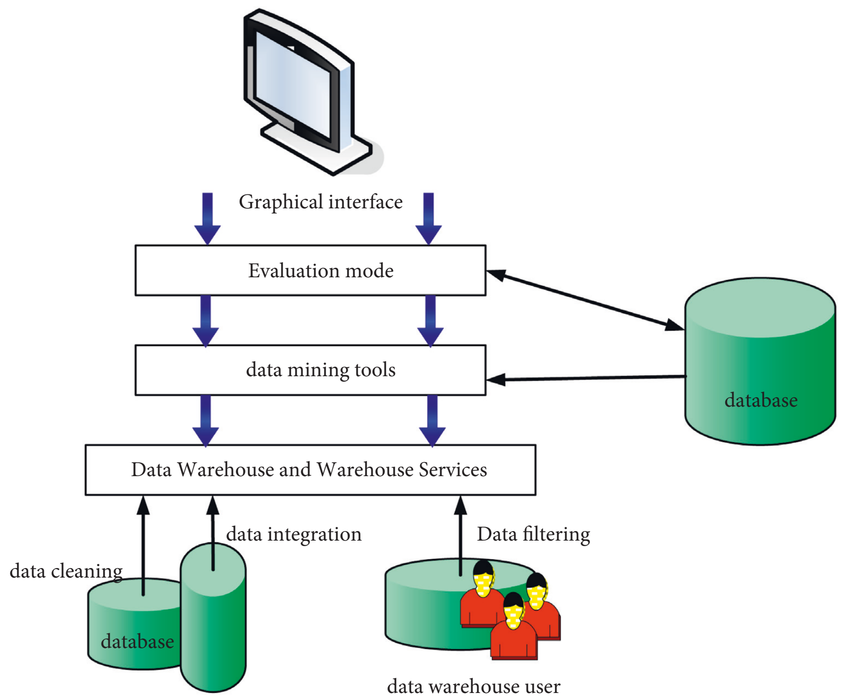

Figure 1: Schematic diagram of data mining architecture.

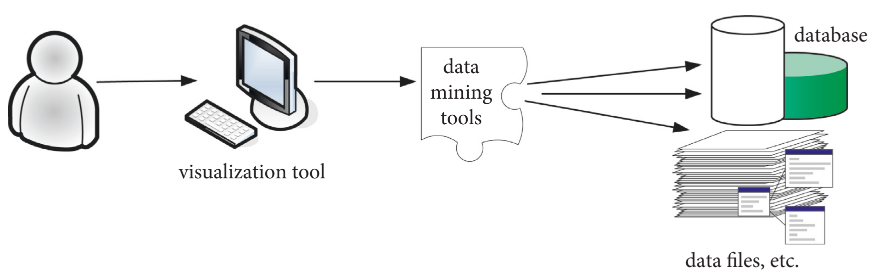

Figure 2: Data mining environment composition diagram.

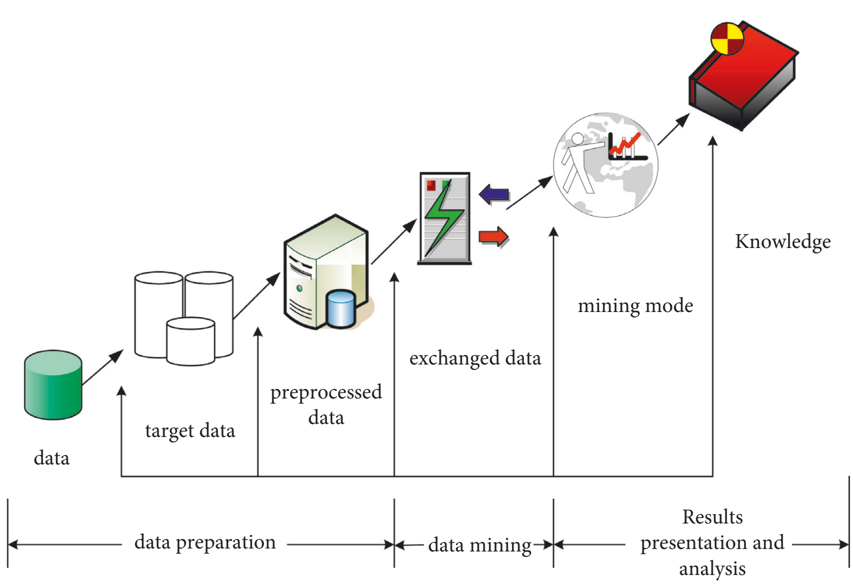

Figure 3: Schematic diagram of the process of data mining.

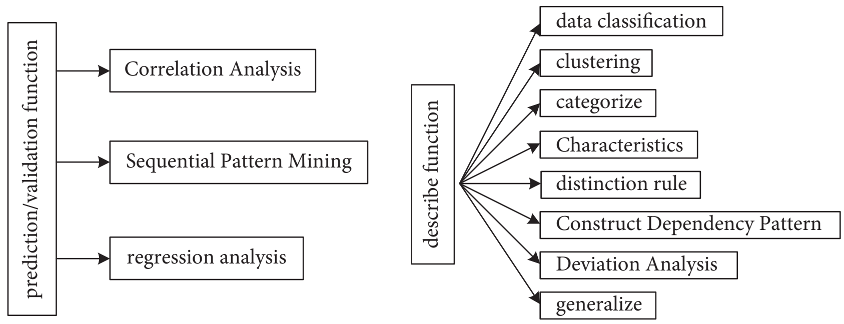

FIGURE 4: Main functions of data mining.

items in a dataset, denoted as F.sunp. Its calculation formula is shown as formula (1):

$$F.\text{sunp} = \frac{\phi i}{|W|}. \quad (1)$$

In formula (1), the total number of transactions in the transaction database is $|W|$. The minimum number of supports is set by the user and can be expressed as min.sunp.

Confidence: Confidence is the probability guarantee that the error between the sampling index and the overall index does not exceed a certain range. As one of the attributes of the association rule, the confidence level in the association rule A⇒B describes the possibility that the transaction in the database contains both A and B. It can be expressed as Conf (A⇒B), and the calculation formula is as formula (2):

$$\text{Conf}\,(A\Rightarrow \text{B}) = \frac{(A\cup \text{B})\text{sunp}}{F.\text{sunp}}. \quad (2)$$

In formula (2), the minimum confidence level is also set by the user and can be expressed as min.Conf.

Frequent itemsets: Suppose an itemset F exists with the relation and then formula (3) and formula (4) can be obtained:

$$\phi i \geq \min.\text{sunp} * |W|, \quad (3)$$

$$F.\text{sunp} \geq \min.\text{sunp}. \quad (4)$$

The itemsets are frequent itemsets or maximum itemsets, and the core content of mining association rules is to find frequent itemsets.

Association rules: Association rules are implications of similar form to A⇒B, where $A \subseteq F$, $B \subseteq F$, and $A \cap B = \Theta$ can describe implicit relationships between data items in a transactional database.

Because the process of generating association rules no longer scans the transaction database, the main work in the mining process is the first step: finding frequent itemsets. The whole process of mining association rules can be simplified as shown in Figure 5.

3. Related Algorithms

3.1. Apriori Algorithm. The association rule algorithm is a two-step mining process: 1. Find a set of frequent items in the transaction database; 2. Generate association rules according to step 1. A priori algorithm is the process of finding the set of frequent items, which is the most important step in the process of mining association rules. Apriori algorithm is one of the most influential algorithms for mining frequent itemsets of Boolean association rules. The core idea is to mine frequent itemsets through two stages: candidate set generation and plot downward closure detection. Its core is a recursive algorithm based on the idea of two-stage frequency sets. The flowchart of this algorithmic process is shown in Figure 6.

The most classic association rule algorithm is the Apriori algorithm. It uses a layer-by-layer search method to find the relationship between items in the transaction database to discover rules. The Apriori algorithm is simple and clear, without complicated theoretical derivation, and it is easy to implement. It consists of join and pruning operations.

Connect operation: Frequent itemsets F-self-connection $H_f \infty H_f$, the necessary condition for the generated candidate frequent itemsets $F+1-$ itemsets G_{f+1}, H_f to be able to connect is that only the current F-1 items are the same.

The set of frequent F-itemsets is as formula (5):

$$H_f = \{h1, h2, \ldots hi\}. \quad (5)$$

If h_i, h_j are, respectively, an item set in H_f, formula (6) and formula (7) are shown as

$$h_i = \left\{h_{i(1)}, h_{i(2)}, \ldots, h_{i(n)}\right\} (1 \leq i \leq n), \quad (6)$$

$$h_j = \left\{h_{j(1)}, h_{j(2)}, \ldots, h_{j(n)}\right\} (1 \leq j \leq n). \quad (7)$$

The itemsets are connectable assuming the form of formula (8) is as follows:

$$\left[h_{i(1)} = h_{j(1)}\right] \wedge \left[h_{i(2)} = h_{j(2)}\right] \wedge \cdots \wedge \left[h_{i(f-1)} = h_{j(f-1)}\right] \wedge \left[h_{i(f)} \neq h_{j(f)}\right]. \quad (8)$$

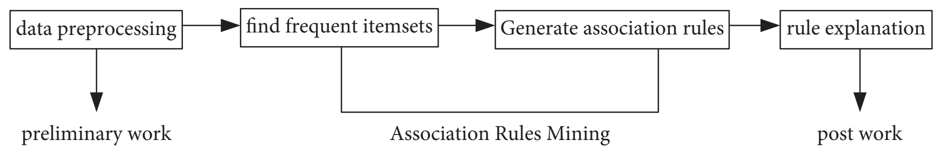

Figure 5: Mining process of association rules.

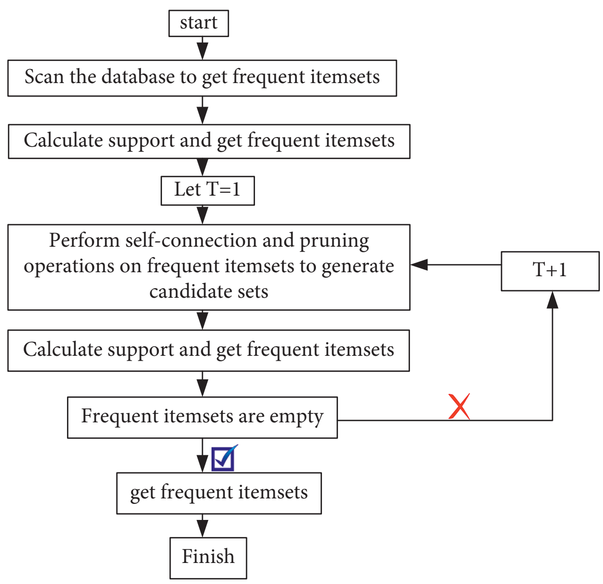

Figure 6: The process of finding frequent itemsets by Apriori algorithm.

An itemset in the set of H_{f+1} itemsets can be obtained by connection, as formula (9):

$$h_m = \left\{h_{i(1)}, h_{j(1)}, \ldots, h_{i(f)}, h_{j(f)}\right\}, h_m \subseteq G_{f+1}. \quad (9)$$

Pruning operation: Since the candidate set of frequent items contains a large number of candidate sets, the transaction database needs to be scanned when calculating its support, so the candidate set needs to be compressed to reduce the number of scans. In short, it is to remove those unnecessary intermediate results.

3.2. According to the Properties of Apriori. Assuming that there is an itemset that is frequent itemset, its nonempty subsets must be frequent itemsets. Therefore, if a k-sub-itemset in a certain $k+1$-itemset in the candidate frequent itemset $\mathrm{Ck}+i$ set is not a frequent itemset, then the candidate $k+1$-itemset in the candidate frequent itemset $\mathrm{Ck}+i$ is removed from the collection. After pruning, the number of candidate frequent itemsets can be reduced to some extent.

3.3. Improved Algorithm. The AprioriTid algorithm adjusts the Apriori algorithm. Its characteristic is that, after traversing the database D for the first time, the database is no longer used to calculate the support, but the set Ck is used to complete it.

The disadvantage of the AprioriTid algorithm is that, in the initial stage of the mining process, since the number of candidate frequent itemsets may be more than the number of data items, the number of items contained in the transaction set in the generated Tid table is much larger than the number of items in the original transaction database.

Suppose there are n records in a transaction database, and the number of transactions contained in the c $(0 \leq c < n)$ record is denoted as $K\_\mathrm{Num}_{(c)}$. If the frequent itemsets obtained from the solution have a total of T orders, the number of candidate frequent sets contained in the $e\,(0 \leq e < = T)$ order is expressed as $\mathrm{ItemNum}_{(e)}$.

If the Apriori algorithm to solve the frequent itemsets in the solution process is used, it can be known that when calculating the support number of each candidate frequent itemset, all transactions in the database need to be scanned each time. The calculation formula of the number of transactions to be scanned in the eth order candidate item set is as formula (10):

$$\mathrm{Num}_{(1)} = \mathrm{Item\_Num}_{(1)} \times \sum_{c=0}^{n-1} K\_\mathrm{Num}. \quad (10)$$

The formula for the number of comparisons for all transactions is as formula (11):

$$\mathrm{Total\_Num1} = \sum_{e=0}^{T} \mathrm{Num}_{(e)}. \quad (11)$$

Assuming that the Apriori algorithm is used to calculate the support number of candidate frequent itemsets, it does not scan the original database but scans the constructed Tid table, which also has T order in the table. Suppose there are $h(e)$ records in the $e\,(0 \leq e < = T)$ order in the table, and the number of itemsets contained in the $c\,(0 \leq c < h_{(c)})$ record is $\mathrm{Tid\_Item\_Num}_{(c)}$. At this time, the calculation formula of the number of itemsets in the scanned table of the candidate frequent itemsets of the eth order is as formula (12):

$$\mathrm{Tid\_Scan\_Num}_{(e)} = \mathrm{Item\_Num}_{(e)} \times \sum_{c}^{h(e)} \mathrm{Tid\_lem\_Num}_{(c)}. \quad (12)$$

The calculation formula for the number of comparisons of all itemsets is

$$\mathrm{Total\_Num2} = \sum_{e=1}^{T} \mathrm{Tid\_scan\_Num}(e). \quad (13)$$

The improved algorithm does not need to scan the original database when calculating the support number of the candidate set but scans the Map table corresponding to the corresponding candidate set, and the calculation equation of the number of candidate frequent itemsets contained in all the hierarchies is as formula (14):

$$\text{Total\_Item\_Num} = \sum_{e=1}^{T} \text{Item\_Num}(e). \tag{14}$$

A single F-order candidate frequent itemset usually consists of two T-1-order frequent itemsets. If the number of IDs in the $c\,(1 \leq c \leq \text{Total\_Item\_Num})$ frequent itemset is $\text{Tid\_Num}(c)$, then the calculation expression equation of the support number of the frequent itemsets of the candidate set is as formula (15):

$$\text{Compare\_Num}_{(c)} = \max\left(\text{Tid\_Num}_{(c)}, \text{Tid\_Num}_{(c2)}\right). \tag{15}$$

The calculation formula of all comparison times is as formula (16):

$$\text{Total\_Num3} = \text{Compare\_Num}_{(c)} \times \text{Total\_Item\_Num}. \tag{16}$$

Through the comparative analysis of all comparison times $\text{Total\_Num}\,(1/2/3)$ by three formulas, $\sum_{c=0}^{n-1} T\text{\_Num}_{(c)}$, $\sum_{e=0}^{n(T)-1} \text{Tid\_Item\_Num}(e)$, and $\max(\text{Tid\_Num}_{(c)}, \text{Tid\_Num}_{(c2)})$ can be compared by simple planning.

In summary, the improved algorithm is feasible. It can improve the running time of the program.

3.4. Algorithm Timeliness Comparison. In order to verify the effectiveness of the time efficiency of the improved algorithm in the case of small transaction differences, 1000 sample data are selected, in which each transaction has little difference. By setting different support degrees, the time required to solve the frequent itemsets of the improved algorithm, Apriori algorithm, and AprioriTid algorithm under different thresholds is calculated. The time required to solve the frequent itemsets is shown in Table 1.

Analysis of Table 1 shows that the improved AprioriTid algorithm based on the Apriori algorithm reduces the running time of the algorithm to a certain extent and improves the time efficiency of the algorithm compared with the execution time of the Apriori algorithm. Compared with the other three algorithms, the improved algorithm has shorter running time and higher efficiency. Overall, it can be seen that the improved algorithm has significant advantages in improving the time efficiency of the algorithm.

Table 1: Algorithm comparison results.

Support	Apriori	AprioriTid	Improved algorithm
0.3	1035.4	823	335.8
0.35	443.6	296.4	195
0.4	222.3	162.8	128.8
0.5	122.5	94.4	73
0.6	74	27.3	18.3
0.7	27.2	19	13

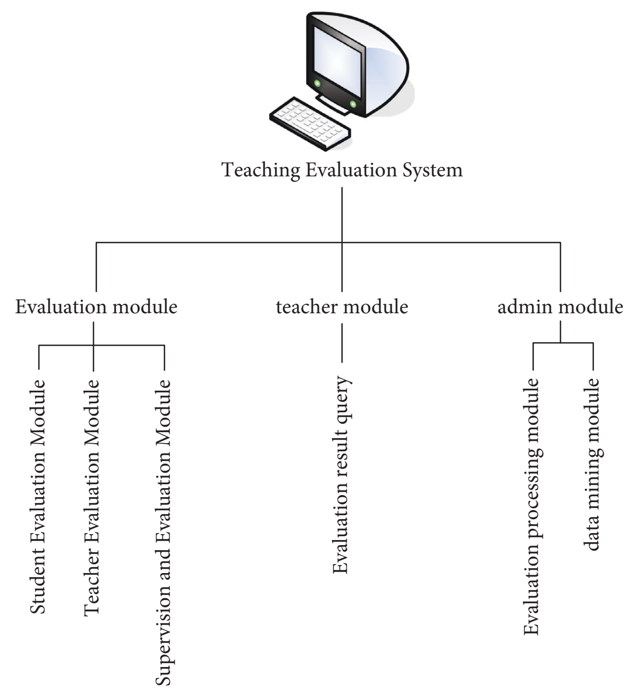

Figure 7: Functional diagram of the teaching quality evaluation system based on association rules.

3.5. Design of Teaching Quality Evaluation System Based on Association Rules

3.5.1. System Function Design. The function of the teaching quality evaluation system based on association rules is shown in the following functional module in Figure 7.

The teacher module is mainly used to query information, i.e., evaluation results. The administrator module includes an evaluation processing module and a data mining module, where the evaluation processing module is used to process the evaluation results. The data mining module is mainly used to combine the evaluation results with various databases in the digital campus to perform data mining on the data and discover hidden potential information.

3.5.2. System Structure Design. The data mining module of the system provides functions such as attribute definition, data extraction, rule mining, and result display, and association rule mining is the core of the system. The architecture is shown as Figure 8.

SQL statement generates module and generates SQL statements to extract data from the database. Then the policy module definition extraction record will be extracted. The data extraction uses the extraction strategy module and the final result of the SQL statement generation module to select specific records and a result display module that outputs the final result from the database module. The result shows that the module is responsible for outputting the final mining rules.

In order to realize the online monitoring and evaluation of the teaching quality of different teachers and to achieve scientific and reasonable course evaluation, the primary task is to establish a database. How to build the database and

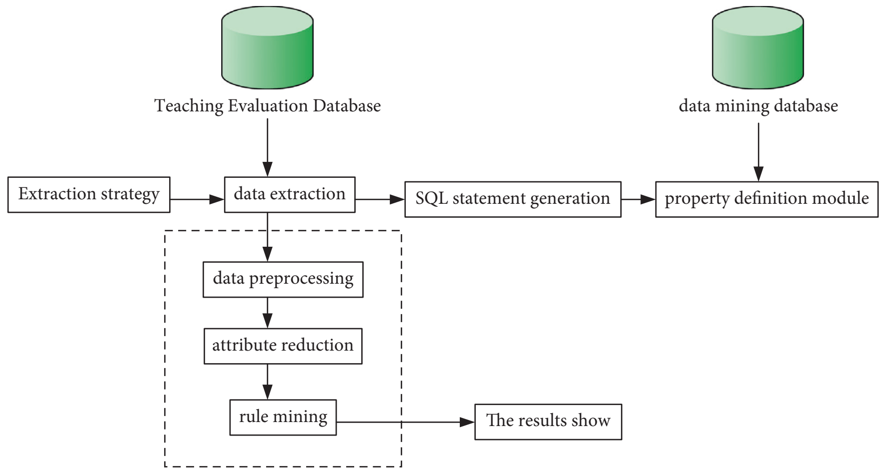

Figure 8: Structure of quality assessment system based on association rules mining data.

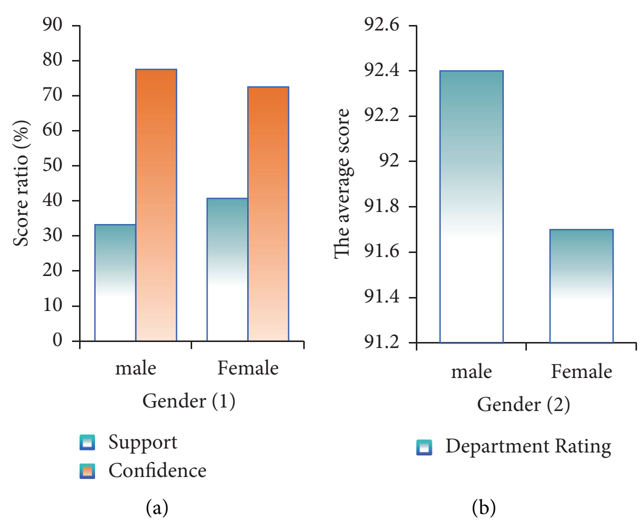

Figure 9: Relationship between teacher gender and teaching quality.

what kind of data structure is used have a direct impact on the efficiency and scientificity of the evaluation. The database designed for this system consists of the five elements listed in Table 2.

After a period of time, or due to student graduation or teacher adjustment, the system administrator can perform some basic operations such as clearing, inputting, modifying, and deleting these tables as required.

3.6. Simulation Experiment. In the experiment of this paper, the student evaluation data within one year is selected as the analysis basis for teaching quality evaluation, and the personal influencing factors of teachers are used as the data mining module. The evaluation data of the management department within the time period is retrieved, converted into scoring results, and formed into graphic data. To further compare the significant differences between teachers' gender and teaching quality, the statistical results are shown in Figure 9.

Figure 9 shows the differences in teaching quality under student evaluation data in relation to gender. From the support as well as confidence data in the figure, the difference in gender does not have much effect on the quality of teaching, indicating that the quality of teaching of teachers is not necessarily related to their gender. Figure 9 shows the mean scores of the teachers' evaluations under the data of departmental evaluations. From the data of the figure, there is a more obvious gender difference in the ratings of teachers by the administration, which may be the result of the different concerns of the administration and the students' concerns.

Set the minimum support and minimum confidence as 5%, and the frequent itemsets in Figure 10 are shown in Table 3.

Figure 10 and Table 3 are the mining results of student evaluation data. It can be concluded that teachers with professional titles of professors and associate professors have good teaching effects, while teachers with professional titles of teaching assistants have only qualified scores, indicating

Table 2: Tables contained in the database.

1. Administrator information sheet	Record administrator name and password
2. Student information sheet	Record student ID, name, password, etc.
3. Teacher information sheet	Record faculty names, departments, etc.
4. Class schedule	Record the class, code, etc.
5. Teacher's evaluation table	Record the scores for each scoring indicator, etc.

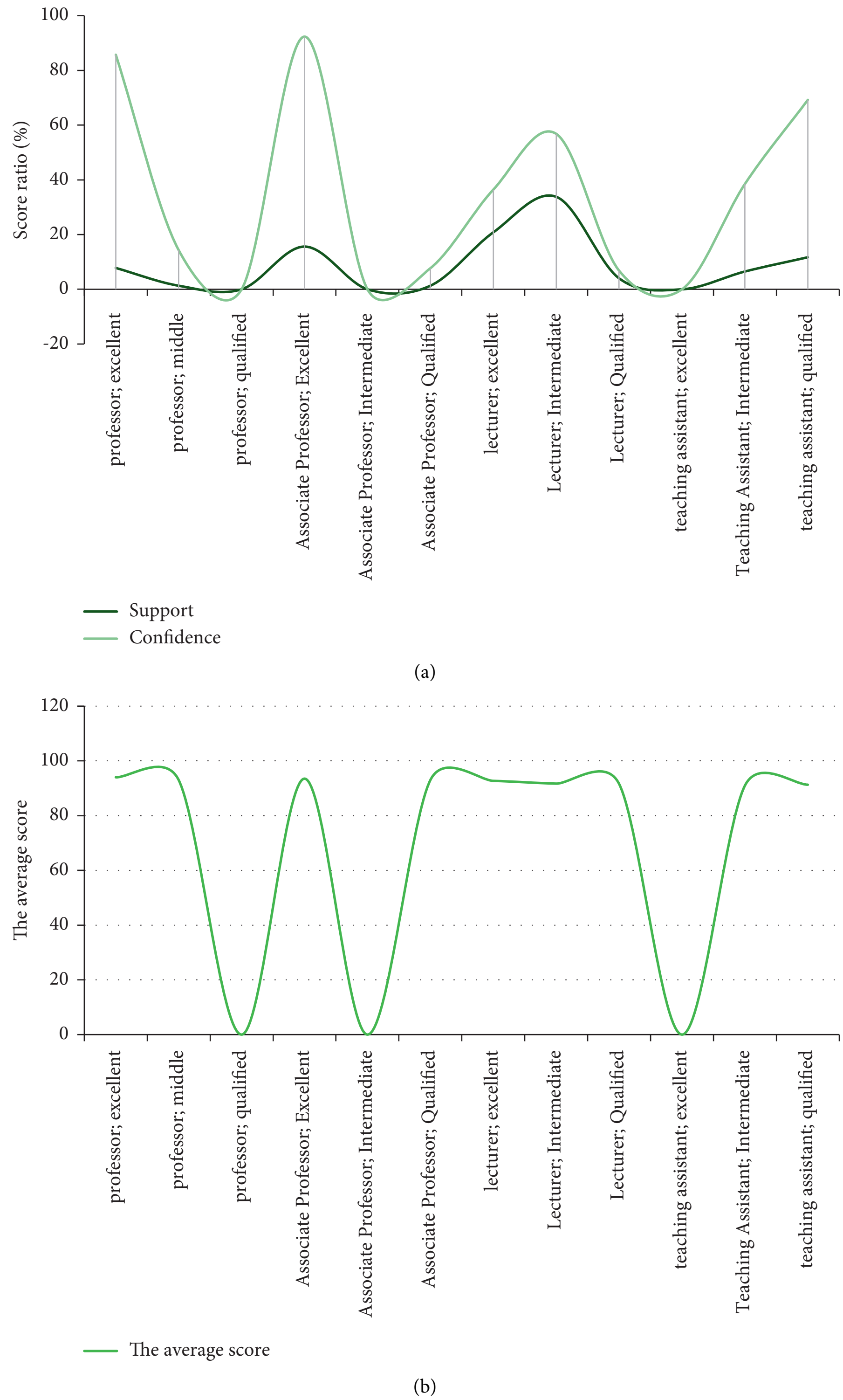

Figure 10: Relationship between teachers' professional titles and teaching quality.

Table 3: 4 frequent items in the itemset.

Frequent itemsets	Number of supports	Support (%)	Confidence (%)
professor = excellent	6	7.8	85.7
Associate Professor = Excellent	12	15.6	92.3
Lecturer = Moderate	25	33.8	56.8
Teaching Assistant = Qualified	8	11.7	69.2

Table 4: Frequent itemsets affected by age.

Frequent itemsets	Number of supports	Support (%)	Confidence (%)
Parent age = medium	10	11.7	50
Middle age = excellent	23	28.6	47.8
Middle age = middle age	21	27.3	45.7
Old age = excellent	10	13	76.9

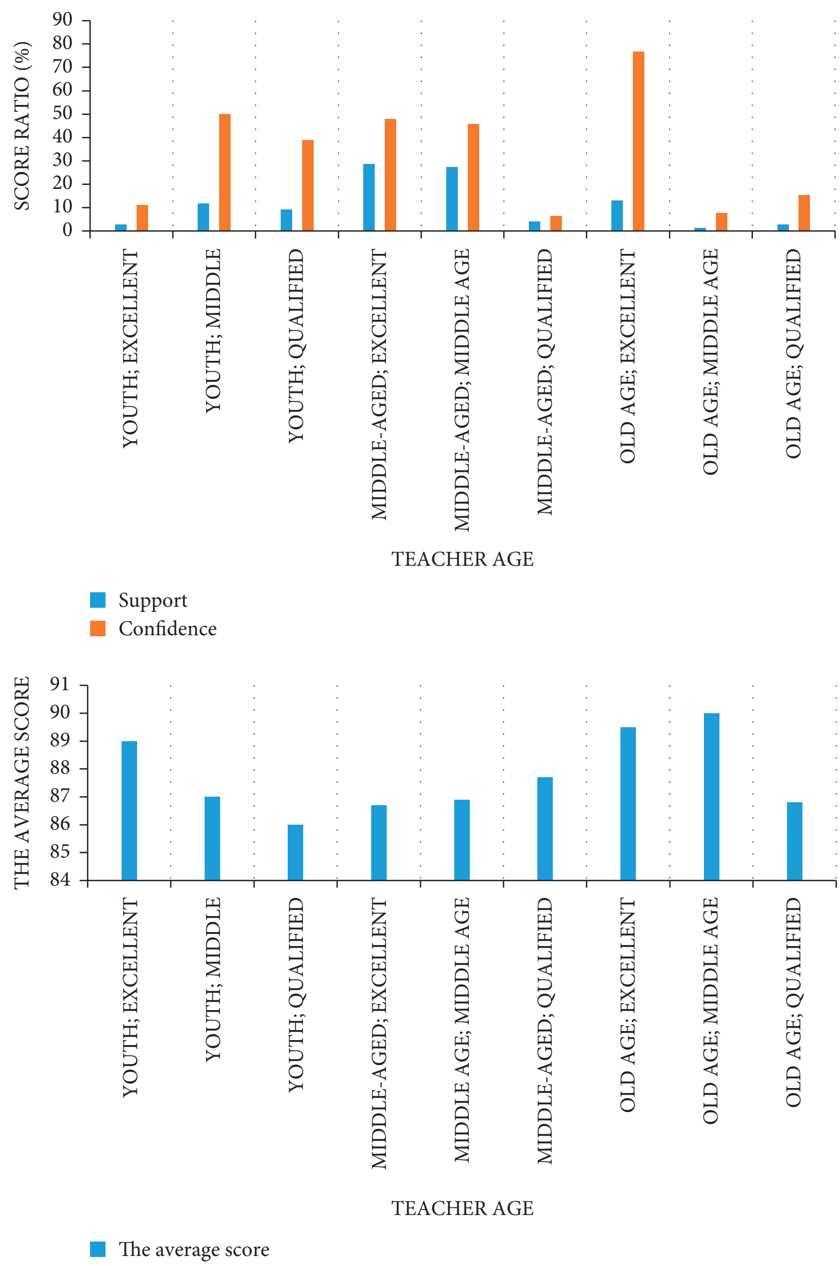

Figure 11: Relationship between teacher age and teaching quality.

Table 5: Frequent itemsets of student grades.

Frequent itemsets	Number of supports	Support (%)	Confidence (%)
excellent = excellent	21	26	62.5
medium = medium	15	18.2	45.2
pass = pass	8	9.1	53.9

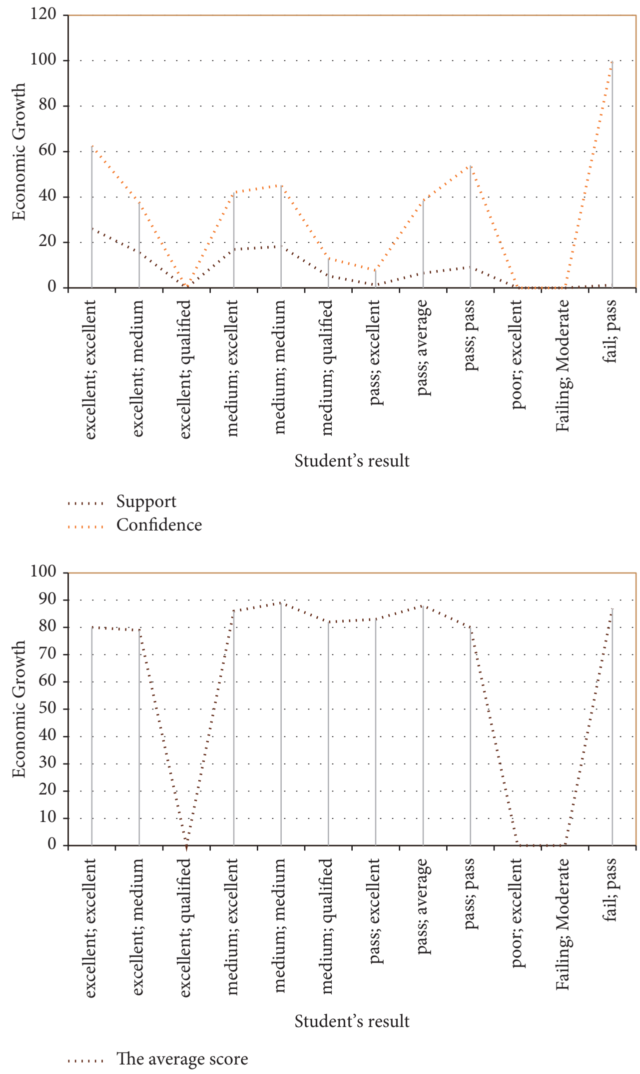

Figure 12: Relationship between student achievement and teaching quality.

that teachers with high professional titles have good teaching effects. Similarly, the relatively low support for the title of professor indicates that the school is in short supply of teachers with the title of professor. The school should increase its efforts to introduce and cultivate teachers with the title of professor to improve the quality of teaching and scientific research. Figure 10 is a statistical graph of the average score of the management department's evaluation data. The average score results are also significantly different. This is because the management department's evaluation of teachers is different from that of students.

Assuming that the minimum support and minimum confidence are 5% and 45%, respectively, the frequent itemsets in the above itemsets are shown in Table 4.

As shown in Figure 11 and Table 4, both the student evaluation results and the management department's average evaluation score clearly show a characteristic; that is, the older the teacher, the better the teaching effect. Among them, students of courses taught by older and middle-aged teachers rate higher, while students of younger and middle-aged teachers mostly rate as medium. To some extent, this means that older teachers have accumulated more teaching experience. Schools can establish a targeted training structure for young and middle-aged teachers. Old teachers can help and guide young and middle-aged teachers, so that young and middle-aged teachers can accumulate teaching experience under the influence of middle-aged and elderly teachers, continuously improve teaching quality, and play an exemplary role.

Assume that the minimum support and minimum confidence are 5% and 45%, respectively. Then the frequent itemsets of the above itemsets are shown in Table 5.

Figure 12 and Table 5 show the evaluation relationship between student performance and teaching quality from the perspective of student data and the management department. The results show that there is a high correlation between students' test scores and their evaluation grades. The average score is excellent, and most of the evaluation scores are excellent. The test score is pass, and most of the evaluation scores are pass. Accordingly, student's grade is proportional to the student's evaluation conclusion of the teacher. The results of students' evaluation of teachers show that the results are true, and the quality of teachers' teaching can be known through students' grades. Furthermore, it shows that the application of data mining techniques to university education can play a positive role in promoting the quality of education and the development of students, individual teachers, and the school as a whole.

4. Conclusions

This paper introduces the relevant knowledge of data mining and data mining taxonomy and analyzes the necessity and importance of applying data mining technology to the information management system of colleges and universities. Methods of applying them to management systems are discussed. The most classic association rule algorithm is the Apriori algorithm, to solve the problem that the number of items contained in the transaction set is much larger than the number of items in the original transaction database in the initial stage of the mining process. Verification by actual data shows that the improved algorithm is more time-efficient. This paper applies data mining techniques in the field of education management to a student assessment database to identify key factors that affect students' overall performance. Data mining of the school teacher database shows that there is no correlation between teaching quality and teacher age, while teachers with higher professional titles and older teachers have better teaching effects, which further shows that teaching quality is positively correlated with it. Through this correlation, it can rationally assign class teachers, stimulate students' learning attitude, and make teaching activities better implemented, which helps to improve the quality of teaching and learning.

Data Availability

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

Conflicts of Interest

The author declares no conflicts of interest.

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