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Application of Data Mining Technology in the Selection of Teaching Evaluation Indicators and the Construction of Teaching Information Evaluation Model in Colleges and Universities

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Abstract
Due to the low efficiency and poor accuracy of current college teaching intelligence evaluation methods, an improved method is proposed. Firstly, an improved apriori (IApriori) algorithm is utilized to filter evaluation indexes and establish a teaching quality evaluation indicator system. Secondly, considering the high complexity and low accuracy of the backpropagation neural network (BPNN), principal component analysis (PCA) is taken to reduce the input data's dimension. An improved sparrow search algorithm (ISSA) is simultaneously utilized to optimize the parameters of BPNN. Finally, a PCA-ISSA-BPNN teaching intelligence evaluation model is constructed. The experiments validated that when the number of transactions was 1,000, the IApriori only took 0.32 seconds to run. While the number of projects was 11, IApriori ran in 15.28 seconds. The evaluation accuracy of the PCA-ISSA-BPNN model reached 99.05%, the F1 value was 96.43%, the recall was 97.26%, and the AUC was 0.981. The above data show that IApriori has a higher efficiency in data mining and can more effectively screen evaluation indicators. This research method can effectively and accurately evaluate teaching quality, and has a positive impact on promoting student development, advancing teaching reform, and improving teaching quality.

Keywords
Apriori, BPNN, Data Mining, SSA, Teaching Evaluation

1. Introduction

In recent decades, information technology, Internet technology, and the Internet of Things (IoT) technology have developed rapidly. These technologies have now become integral to all walks of life, as well as all aspects of people's lives [1]. Therefore, there is abundant information and data stored in different industries and fields. With the digital transformation of universities, information-based teaching has been realized in China's universities. The higher education institutions' management system stores numerous teaching information data, such as students' grades, teachers' qualifications, teaching courses, etc. However, these valuable data have not been analyzed and fully utilized to a large extent, resulting in extremely low data utilization rates that cannot support the development and reform of university teaching [2]. Data mining (DM) technology is a data processing and analysis technology that can mine

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the implicit relevance in big data. DM enables the extraction of the implicit information in the information data, thereby significantly improving the utilization rate of the information data [3]. Many scholars have employed DM techniques to analyze college teaching data and evaluate teaching quality. This approach can help teachers recognize the shortcomings in teaching and contribute to the reform of university teaching models and the improvement of university teaching quality [4, 5]. There are two constraints in the current evaluation methods of teaching quality in universities. The first is the inappropriate selection of evaluation indicators, resulting in a low accuracy rate of teaching quality evaluation (TQE). The second reason is that the evaluation efficiency is low and requires more time. To address the above problems, a method for selecting TQE indicators based on an optimized K-means clustering is designed. Meanwhile, this paper also proposes an improved backpropagation neural network (BPNN) to achieve smart TQE. The study has two main innovations. The first is to use the improved apriori (IApriori) to screen evaluation indicators for teaching quality in universities and improve the rationality of indicator selection. The second point is to achieve intelligent TQE based on the improved BPNN. The main structure of the study is separated into four sections. Section 2 is a discussion of the latest relevant research. Section 3 implements the indicator selection of college TQE based on IApriori, and constructs an intelligent evaluation model combined with improved BPNN. Section 4 analyzes the performance of the intelligent TQE model. Section 5 is a summary of the entire study.

2. Related Works

With the rapid development of information technology, the Internet and the IoT, massive data in different fields and industries are accumulating. DM technology can process and analyze these huge amounts of information data. It can obtain effective information contained in data based on the analysis results, thereby improving the utilization efficiency of information data, and mining implicit relationships between data. Recent studies have shown various applications of DM technology. For example, Andriani et al. [6] combined DM methods based on the cluster analysis to explore the role of quantum size effects in CH4 dehydrogenation on 3D transition metal clusters. Wang and Smys [7] proposed a method of big data analysis and perturbation. This method used DM algorithms to mine the correlation between big data, analyzes big data according to the mining results to obtain implicit information in big data. Aziz and Aftab [8] conducted a random survey to obtain dietary information data from the respondents. They used DM technology to rank the nutritional coefficients of the respondents' diets, thereby recommending a reasonable dietary structure for people. Mengash [9] used DM technology to analyze students' relevant data. They used the analysis results to predict the students' learning performance, thereby helping to complete the university admission work. Edastama et al. [10] designed an IApriori and used it to perform DM on the sales of eyeglasses. The factors that attract customers to make consumption behavior were obtained, and the sales volume of eyewear stores was increased. Sinaga et al. [11] used C4.5 algorithm to achieve DM on customers, thereby predicting customer satisfaction. This provided data support for product quality improvement and service quality improvement. The recall rate of this method reached 0.978. Sulaiman [12] proposed a variety of DM and data classification methods, and applied these DM and classification methods to IoT. By comparing the performance of these DM classification methods, the utilization efficiency of IoT data has been improved, which has a catalytic effect on the development of the IoT. El Aouifi et al. [13] combined k-nearest neighbor algorithm and multilayer perceptron algorithm to mine educational data and analyze learners' video sequence viewing behavior. In accordance with analysis results, they predicted learners' learning performance to facilitate teachers' reasonable and effective teaching guidance.

Teaching evaluation is an essential path for teachers to discover and solve teaching problems, thereby achieving teaching reform and improving teaching quality. By mining teaching data and analyzing the potential connections between data, TQE can be achieved. Huang [14] designed a machine learning model based on Gaussian process and applied it to the English TQE. The accuracy and efficiency of this model could meet the requirements, and it had high practicality. Tang [15] applied intelligent learning technology to propose a quality evaluation technology for online course teaching, thereby achieving intelligent evaluation of the online course quality to promote the development and improvement of online teaching. Wang [16] put forward a CODAS method based on interval valued intuitionistic fuzzy information to intelligently evaluate the College English Teaching (CET) quality. This was conducive to the innovation of CET. Gao [17] suggested a Clementine-based DM technology and applied it to the evaluation of CET ability. This technology provided a lateral assessment of the quality of CET and elaborated the direction for improving the ability of college English teachers. Ali et al. [18] designed a weighted interval valued dual hesitation fuzzy set and applied the method to the TQE. This improved the accuracy of TQE. Link et al. [19] used computer technology to achieve automated and intelligent writing evaluation, and explored the impact of writing evaluation on teacher feedback, student review, and writing improvement. Guo [20] combined DM technology and decision tree models to build an intelligent model. The factors influencing the teaching effectiveness of dance courses in universities have been analyzed. Based on artificial intelligence technology, Sun et al. [21] designed an online intelligent English teaching platform. This platform could conduct intelligent evaluation of English teaching, thereby improving the teaching quality and improving the students' English proficiency.

In conclusion, the current intelligent evaluation technology for teaching quality combined with DM technology has been very popular and has achieved certain results. However, the efficiency of the current intelligent TQE models are not ideal. As a result, the evaluation results cannot provide correct feedback to teachers, and the improvement effect on TQE is not obvious. Given this, the paper proposes the DM of IApriori to filter teaching evaluation indicators, and implements intelligent TQE based on improved BPNN. The study aims to effectively improve the TQE accuracy and promote the teaching reform process. The comparison of different studies is shown in Table 1.

Table 1. Comparison of different studies

Study	Year	Result
Edastama et al. [10]	2021	Increased store sales
Sinaga et al. [11]	2021	The recall rate of this method reaches 0.978
Sulaiman [12]	2020	Improved utilization efficiency of IoT data
El Aouifi et al. [13]	2021	Promote reasonable and effective teaching guidance from teachers
Huang [14]	2021	High practicality
Tang [15]	2020	Realized intelligent evaluation of online course quality and promoted the development of online teaching
Wang [16]	2021	Promoting Innovation in CET
Gao [17]	2020	Improving the teaching ability of college English teachers
Ali et al. [18]	2021	Improved the accuracy of TQE
Sun et al. [21]	2021	Improving teaching quality and improving students' English proficiency

3. TQE Model Based on DM and Improved BPNN

3.1 DM-based Index Filtering

In the higher education system, TQE is an essential means to help teachers understand the shortcomings in teaching. It is also an essential method for teachers to achieve self-supervision and self-regulation, thereby improving teaching models and improving teaching quality. Recent years, the higher education reform has been gradually deepened, and the association rule technology in DM has been used to search the correlation between different indicator data. Consequently, building a more scientific and reasonable TQE system has become a crucial task in teaching reform. As an efficient data processing approach, DM technology can obtain the types of data required by users from a mass of information data. The basic process is shown in Fig. 1.

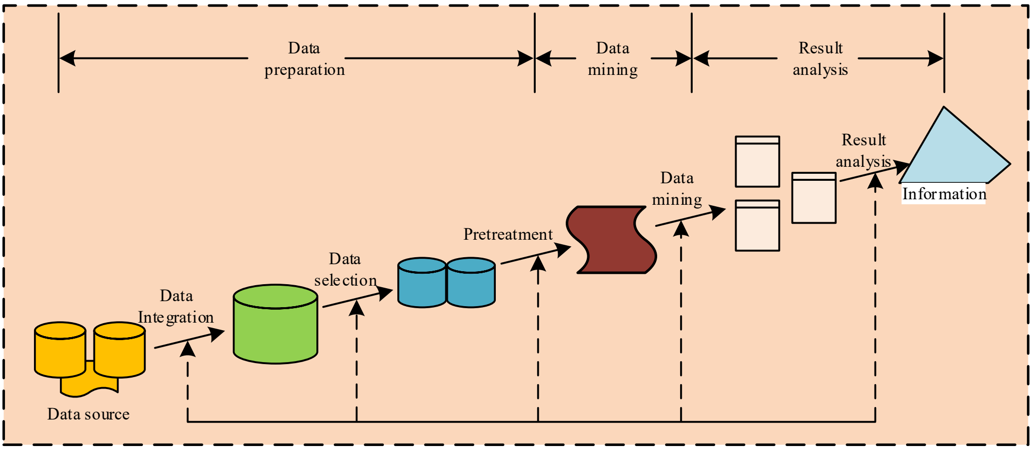

Fig. 1. General process of data mining.

The DM process consists of three parts: data preparation, DM, and result analysis. The data preparation stage involves first integrating the data source and then filtering the data. Next, the filtered data are pre-processed to complete DM. Finally, the results are analyzed to obtain the necessary information. DM is used to screen TQE indicators. The principle is to extract the corresponding data related to teaching quality from the database through corresponding DM algorithm models, and extract the attribute characteristics of the data. According to these data characteristics, an association rule library is constructed for association rule analysis. Then, the correlation between the characteristics of various types of data and teaching quality is obtained based on the analysis results. The research selects Apriori algorithm to implement the above content. Apriori is a widely used DM algorithm currently. However, to ensure accuracy, Apriori will repeatedly scan all things in the database during the iteration process, which will affect the efficiency of the Apriori to some extent. To address this challenge, the study introduces the idea of parallel computing to enhance the algorithm's performance. At this time, if the sum of parallel computing tasks is v and the completion is i, the task to be processed is t_i, then Formula (1) is the total time it takes to complete all tasks.

$$T = \max\{t_1, t_2, \dots, t_i, \dots, t_v\} \tag{1}$$

In addition to the repeated scanning of transactions in the database, Apriori also performs repeated calculations on transactions, resulting in lower efficiency of its DM. If there is a transaction set that contains n transactions, the average length of each transaction is φ. At this point, the Apriori algorithm needs to be scanned $n \cdot \varphi$ times in the transaction set. At this point, in the candidate k-itemset C_k generated during the iteration process of the algorithm, when mining frequent k-itemsets, the number of accesses T_k can be calculated using Formula (2):

$$T_k = n \cdot \varphi \cdot |C_k| \tag{2}$$

After performing N copy operation on this transaction set, a new transaction set is obtained. At this time, the access times T_{Nk} of this transaction set are calculated by Formula (3):

$$T_{Nk} = N \cdot n \cdot \varphi \cdot |C_k| \tag{3}$$

In Apriori, while mining frequent k-itemsets, it is also necessary to remove invalid transactions that do not contain frequent items. In addition to the above operations, duplicate valid transactions should also be compressed. If the effective transaction repetition rate in the transaction set is μ, the algorithm can calculate the effective access times T_{new} through Formula (4):

$$T_{new} = \mu \cdot T_k \tag{4}$$

In response to the above, research has been conducted to optimize the encoding and conversion, hash storage, and transaction compression aspects of Apriori. First, Fig. 2 shows an improvement on the encoding and conversion method of Apriori algorithm.

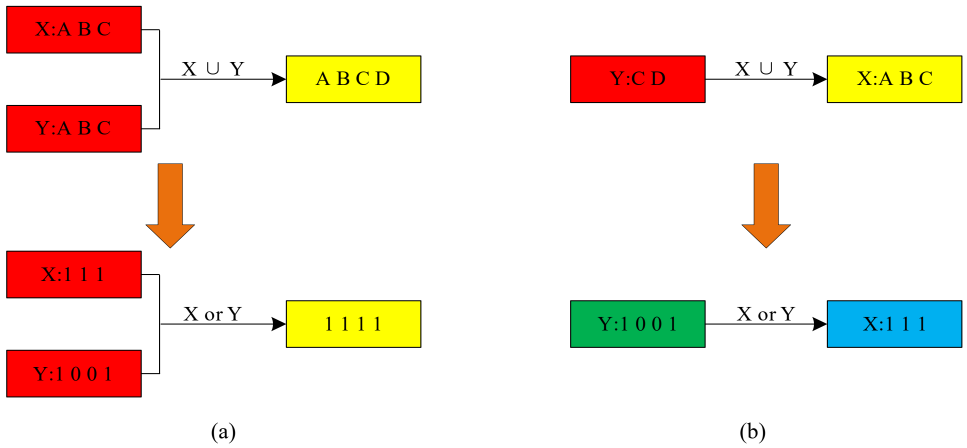

Fig. 2. IApriori algorithm for encoding conversion: (a) the union of itemsets is converted to binary sum “and”, (b) the intersection of itemsets is converted to binary phase "or".

Frequent itemsets $X = \{A, B, C\}$ and $Y = \{A, B, C\}$ are merged to obtain the form of $\{A, B, C, D\}$, which is converted into binary sum $(X, Y) = 1111$. The intersection of itemsets $X = \{A, B, C\}$ and $Y = \{A, B, C\}$ is converted into binary phase or, resulting in $X = 111$ or $Y = 1001$. At this point, for any candidate itemset C_k that exists in the transaction set, its support degree $Support_{mm}$ is calculated by Formula (5).

$$Support_{mm} = \sum_{i=1}^{n} w_i \tag{5}$$

In Formula (5), w_i is the weight value of transaction i. For two frequent $(k-1)$-itemsets L_i and L_j that are different and only differ by one item, the candidate itemsets obtained through the join operation are represented by Formula (6):

$$C = \sum_{i=1,j=1}^{m} L_i \vee L_j \tag{6}$$

In Formula (6), m refers to the number of frequent $(k-1)$-itemsets: $L_i \vee L_j$. The above operation completes the encryption transformation. Using the hash map in the hash store, the transaction set and item set are obtained after the encoding transformation is stored. This approach allows Apriori to repeatedly scan transactions in the database without requiring high frequency during the iteration process. In addition, the hash mapping can store and retrieve all transactions and item sets, allowing for more efficient DM. The above content can store the mapping relationship between transactions and weights, as well as the mapping relationship between transactions and item counts. By storing this mapping relationship, repetitive transactions can be compressed, thereby reducing the number of cycles traversed by the Apriori during the iteration process, and improving DM efficiency. In the above transaction compression, there are three stages in total. The first stage is to set an appropriate support threshold based on actual needs and eliminate transactions below that threshold during the encoding stage. In the second stage, duplicate transactions are compressed into one during hash map storage. The third stage is to filter out transactions whose transaction count is lower than the number of iterations of the Apriori during the DM process. In the second and third stages described above, the calculation of transaction compression support and itemset support is shown in Fig. 3.

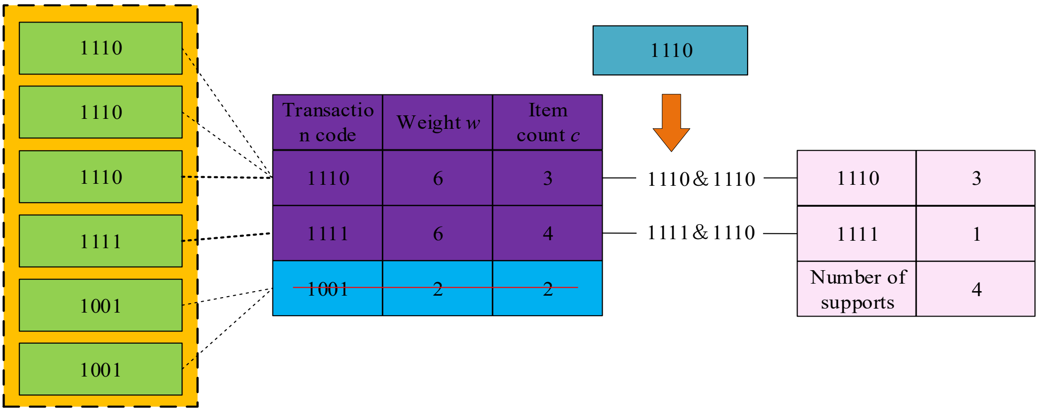

Fig. 3. Support calculation for transaction compression and itemset.

The above method can improve Apriori and build an IApriori. The IApriori is used to calculate the correlation strength between various data in the database and the teaching quality. Data types whose correlation strength is higher than a set correlation strength threshold are used as evaluation indicators. The selection of TQE indicators based on DM is completed.

3.2 Construction of TQE Model based on Improved BPNN

In the previous content, the study used IApriori to screen TQE indicators. According to the selected indicators, the university TQE index system was constructed. Table 2 shows the details.

The expert scoring method and fuzzy comprehensive evaluation determine each indicator's weight. A questionnaire based on Table 2 is developed, and students are asked to grade corresponding courses through the teaching system of universities. In accordance with the weight of each indicator and the scores of students, the TQE data of the corresponding courses are obtained. The study uses the BPNN model to implement TQE to enhance the efficiency of TQE. However, Table 2 contains plenty of indicators, totaling 12. If the model inputs these indicators, it needs to construct 12 input nodes, which may lead to an overly complex network structure of the model, causing a negative impact on the convergence accuracy. As a result, the study uses PCA to reduce the dimension of the input vector to optimize the TQE in line with BPNN and increase the precision. First, the maximum and minimum method is used to normalize all the data, as shown in Formula (7):

$$X = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \tag{7}$$

Table 2. Evaluation index system of university TQE

First-level indicators	Code	Secondary indicators	Code
Teaching attitude	X1	Serious and responsible	Y1
		Emphasize student issues and opinions	Y2
		Attend and dismiss classes according to the system	Y3
		Teaching is full of vitality	Y4
Content of courses	X2	Meet the syllabus	Y5
		Moderate difficulty in teaching content	Y6
		Highlight the teaching focus	Y7
Teaching method	X3	Using modern technology	Y8
		Teach students built on their aptitude	Y9
		Pay attention to the cultivation of students' comprehensive abilities	Y10
Teaching effectiveness	X4	Student average score	Y11
		Student preference	Y12

In Formula (7), X is the data obtained after normalization processing; $I_{\min}$ is the minimum score; $I_{\max}$ is the maximum score; and I is the data value before processing. Then, the indicator system (Table 2) is subjected to factor analysis to obtain four common factors. Table 3 shows their contribution rates.

Table 3. Contribution rate of common factors

Composition	Initial characteristics			Extract the sum of the load squares		
	Total	Percent variance (%)	CCR (%)	Total	Percent variance (%)	CCR (%)
1	4.372	36.433	36.433	4.372	36.433	36.433
2	2.852	23.767	60.200	2.852	23.767	60.200
3	1.666	13.885	74.085	1.666	13.885	74.085
4	1.352	11.267	82.352	1.352	11.267	82.352

The total cumulative contribution rate (CCR) of the four common factors extracted in Table 3 exceeded 82.3%. Due to factor analysis, four common elements were identified. This indicated that the common factors extracted from the study could comprehensively reflect the actual teaching quality situation. By constructing a factor component matrix, the correlation between each evaluation index and four common factors could be obtained, and then corresponding indicators that can represent the common factors could be found. The factor component matrix is shown in Table 4.

In Table 4, the four indicators that can map common factors are Y12, Y11, Y7, and Y5. These four indicators are input into the model as input data. The selection of the weight and threshold parameters of the BPNN has an effect on the model performance. To further improve the performance of BPNN, research has proposed using sparrow search algorithm (SSA) to gain the best parameters of the model. However, the optimization ability and convergence performance of general SSAs are poor, so research has proposed strategies to improve SSAs and optimize their performance. Firstly, a reverse learning idea is introduced to enhance the diversity of the primary sparrow population, such as Formula (8):

$$X_{i,j}^{*} = ub_{i,j} + lb_{i,j} - X_{i,j} \tag{8}$$

In Formula (8), $X_{i,j}$ is a randomly generated initial population. $X_{i,j}^{*}$ is the inverse solution obtained through calculation. $ub_{i,j}$, $lb_{i,j}$ are the maximum and minimum value of dimension j of sparrow i. The fitness values of all sparrows are calculated. When a sparrow individual satisfies Formula (9), the individual is retained as part of the primary population.

$$fit\left(X_{i,j}^{*}\right) < fit\left(X_{i,j}\right) \tag{9}$$

The above operations can enhance the search scope of SSA, thereby enhancing its global optimization capabilities. A nonlinear weighting factor λ is introduced to optimize the location update strategy (LUS) of finders in the sparrow population. λ is determined by Formula (10):

$$\lambda = (t/T_{\max})^2 \tag{10}$$

The t in Formula (10) is the iteration number of the algorithm. $T_{\max}$ is the set iteration upper limit. The improved discoverer LUS is shown in Formula (11):

$$X_{i,j}^{t+1} = \begin{cases} \lambda X_{i,j}^{t} & \text{if } R_2 < ST \\ X_{i,j}^{t} + Q & \text{if } R_2 \geq ST \end{cases} \tag{11}$$

In Formula (11), $X_{i,j}^{t}$ is the position of dimension j of sparrow i after iteration t. Q is a random number that obeys a normal distribution. R_2 is the alert value after iteration t times. ST is the alert threshold set built on the actual situation. The LUS of Formula (11) can improve the SSA's convergence and search performance at the iteration beginning, as well as its global search ability at the end of the iteration. The above content can build a smart assessment model for teaching quality based on PCA-ISSA-BPNN to improve the objectivity and effectiveness of TQE. As a result, the teaching reform in universities has been promoted, and the quality of teaching has been improved.

Table 4. Factor component matrix

Indicator code	Common factor			
	1	2	3	4
Y1	0.133	0.150	-0.102	-0.034
Y2	0.152	0.312	0.044	0.352
Y3	0.140	0.333	0.521	0.068
Y4	-0.213	-0.168	0.142	0.163
Y5	0.362	0.258	0.105	0.907
Y6	0.148	0.369	0.144	0.204
Y7	0.093	0.144	0.915	0.153
Y8	-0.085	0.252	0.144	-0.152
Y9	0.144	0.163	0.108	0.088
Y10	0.352	0.180	-0.053	0.135
Y11	0.937	0.144	0.062	0.142
Y12	0.098	0.918	0.189	0.168

4. Performance Analysis of PCA-ISSA-BPNN TQE Model

The paper obtains data from a university's teaching system and constructs an experimental dataset to test the PCA-ISSA-BPNN's performance. In BPNN, the epochs are 40, the learning factor is 0.0002, and the input, output, and hidden layers are 1, 1, and 20. In the experiment, 60% of the dataset is separated into training sets and the remaining 40% into test sets. To verify the DM performance of IApriori, it is used to compare it with frequent pattern growth (FP-growth) algorithm and traditional Apriori algorithm. First of all, the data in the training set is filtered and two datasets are constructed: a dense dataset and a sparse dataset, each containing 6,000 pieces of data. The runtime of several algorithms under different minimum support settings is shown in Fig. 4. On the dataset in Fig. 4, the DM algorithm takes relatively less time. On the dense dataset in Fig. 4(a), when the minimum support level (MSL) is set to 0.44, IApriority needs to run for 2.32 seconds, which is 5.47 seconds less than FP-growth and 11.31 seconds less than Apriori. On the sparse dataset in Fig. 4(b), when the MSL is 0.037, IApriority needs to run 8.29 seconds, which is 17.08 seconds less than FP-growth and 263.48 seconds less than Apriori.

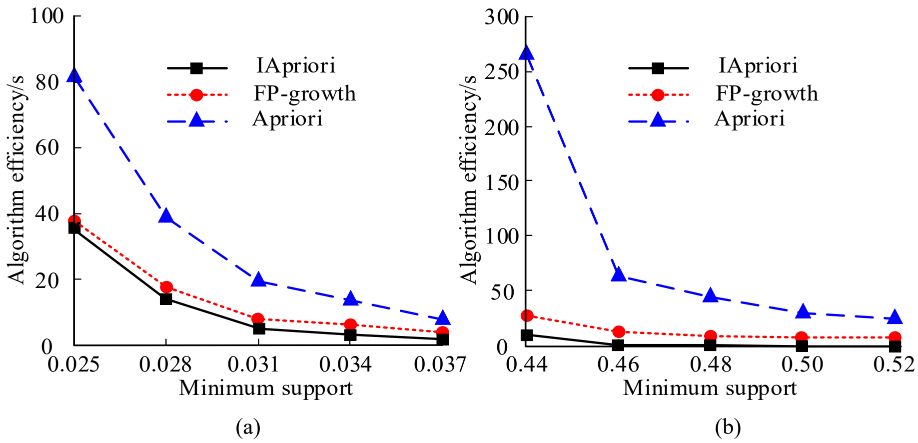

Fig. 4. Running time of the algorithm: (a) intensive dataset and (b) sparse dataset.

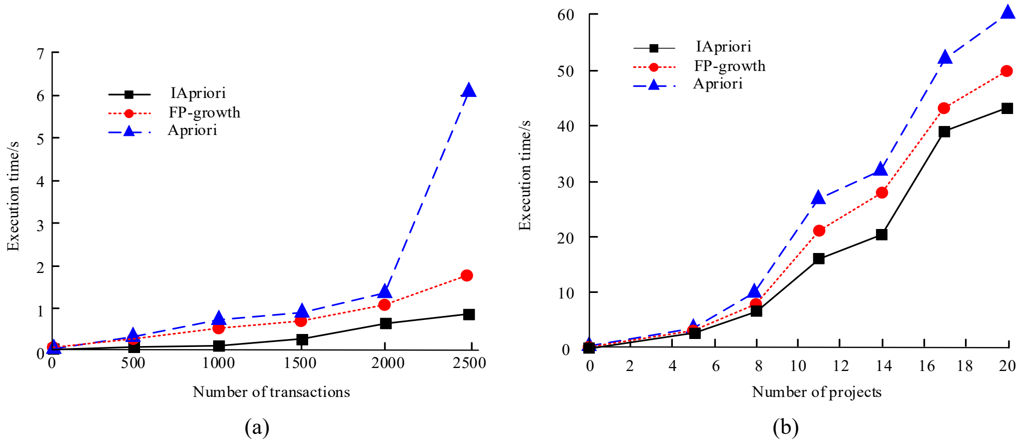

Fig. 5. The runtime under various transaction and item numbers: (a) number of different transactions and (b) number of different projects.

Fig. 5 shows the algorithm's runtime when transactions and items numbers that the algorithm needs to process is different. In Fig. 5, the more transactions and items the algorithm needs to process, the longer the algorithm runs. This is because as the number of transactions and items increases, the amount of data that the algorithm has to process increases, and so does the processing time. In Fig. 5(a), when the pending transactions number is 1,000, IApriority needs to run for 0.32 seconds, which is 0.38 seconds less than FP-growth and 0.81 seconds less than Apriori. In Fig. 5(b), when the number of items to be processed is 11, IApriority needs to run for 15.28 seconds, which is 5.78 seconds less than FP-growth and 12.07 seconds less than Apriori. In summary, the improvement strategies can effectively improve the performance and DM efficiency of Apriori.

To achieve smart and efficient TQE in universities, a PCA-ISSA-BPNN model is constructed. The advanced intelligent models for teaching quality are the GA-SVM and the WOA-BPNN. Fig. 6 is a training set used to verify the convergence of the above three models. In Fig. 6, when the minimum error is reached, the PCA-ISSA-BPNN requires 39 iterations, which is 25 and 64 fewer iterations than the WOA-BPNN and the GA-SVM models. In addition, the minimum error of PCA-ISSA-BPNN is also lower than that of WOA-BPNN and GA-SVM. The data indicate that PCA-ISSA-BPNN has better convergence and can finish smaller errors faster.

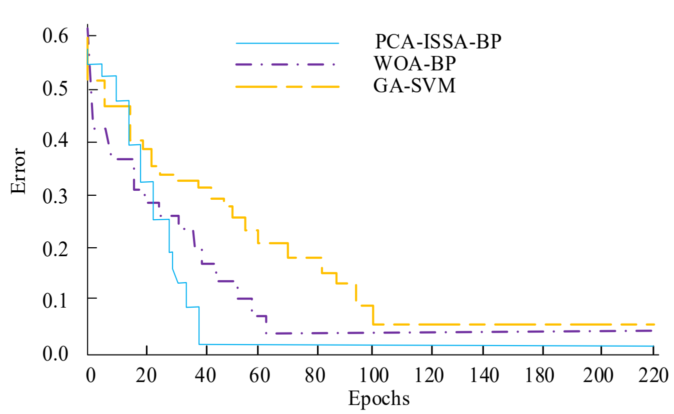

Fig. 6. Convergence of three models.

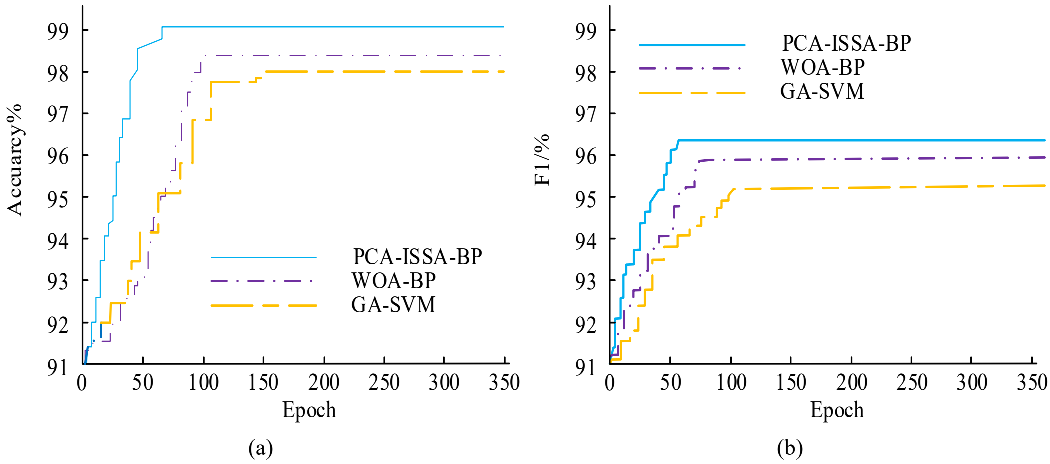

Fig. 7. TQE performance results of three models: (a) accuracy and (b) F1 value.

The test set is used to compare the TQE performance of PCA-ISSA-BPNN, WOA-BPNN, and GA-SVM. The evaluation accuracy and F1 value are chosen as the performance indicators for TQE. Fig. 7 shows the TQE performance of PCA-ISSA-BPNN, WOA-BPNN, and GA-SVM. In Fig. 7(a), the accuracy of PCA-ISSA-BPNN reaches 99.05%, which is 0.63% and 1.06% higher than that of WOA-BPNN and GA-SVM. In Fig. 7(b), the F1 value of PCA-ISSA-BPNN is 96.43%, which is 0.42% and 1.36% superior to WOA-BPNN and GA-SVM. The above results indicate that PCA-ISSA-BPNN performs better in TQE.

Fig. 8 is a comparison of recall values for PCA-ISSA-BPNN, WOA-BPNN, and GA-SVM using a test set. As the iteration increases, the overall recall of the three models shows a rising trend. When the overall recall rises to a certain extent, the recall does not change significantly, and the trend gradually stabilizes. At this point, the model performance has reached its optimal level, and it is no longer possible to improve the performance by iterative updates. The recall of PCA-ISSA-BPNN reaches 97.26%, 1.06% and 3.14% higher than WOA-BPNN and GA-SVM. The above data prove that the PCA-ISSA-BPNN model performs greater than the other two models.

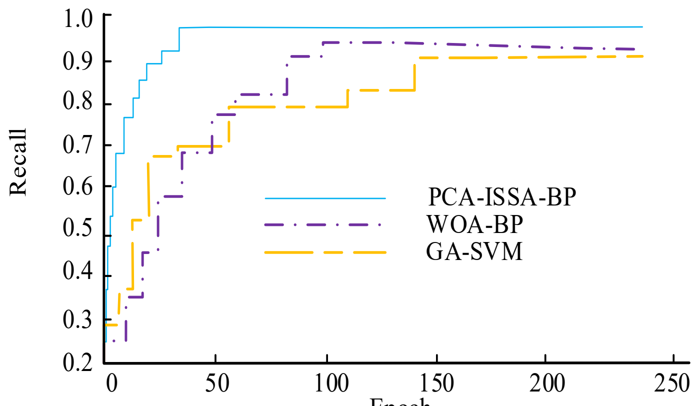

Fig. 8. Recall value of three models.

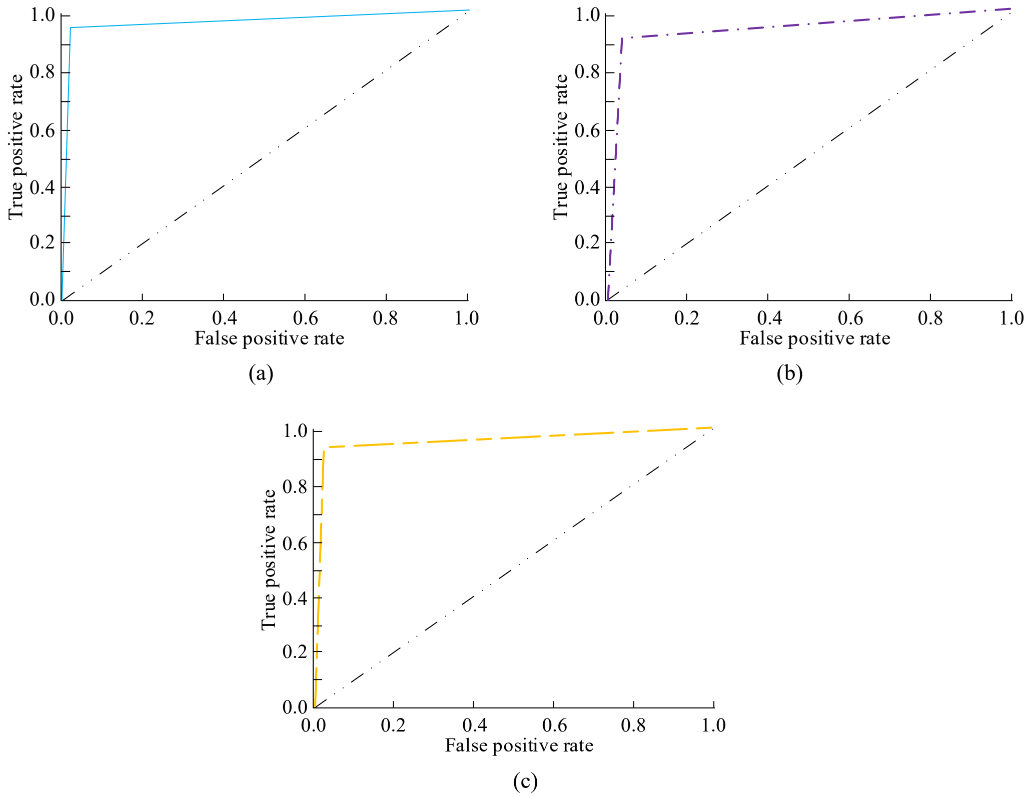

Fig. 9. AUC value of three models: (a) PCA-ISSA-BP, (b) GA-SVM, and (c) WOA-BPNN.

The trend change of the ROC curve is used to evaluate the comprehensive performance of PCA-ISSA-BPNN, WOA-BPNN, and GA-SVM, as shown in Fig. 9. The area under the curve (AUC) of PCA-ISSA-BPNN reaches 0.981, which is 0.012 and 0.025 outperforming than WOA-BPNN and GA-SVM. This indicates that the comprehensive performance of PCA-ISSA-BPNN is more excellent. In conclusion, PCA-ISSA-BPNN can effectively realize intelligent TQE in universities and enhance the rationality and effectiveness of teaching evaluation. At the same time, it can further promote teaching innovation, improve teaching quality, and have a positive impact on students' development.

5. Conclusion

Currently, intelligent TQE in institutions of higher education is very significant. It helps teachers' self-supervision and self-regulation, thereby achieving improvement in teaching models. The study proposed the IApriori screening evaluation index and constructed a PCA-ISSA-BPNN model for teaching quality. Experiments have shown that on dense datasets, when the MSL was 0.44, IApriori needed to run for 2.32 seconds, 5.47 seconds, and 11.31 seconds less than FP-growth and Apriori. On sparse datasets, when the MSL was 0.037, IApriori needed to run for 8.29 seconds, 17.08 seconds, and 263.48 seconds less than FP-growth and Apriori. When the transaction number was 1,000, IApriori needed to run for 0.32 seconds, which was 0.38 seconds less than FP-growth and 0.81 seconds less than Apriori. When the project number was 11, IApriori took 15.28 seconds to run, which was 5.78 seconds and 12.07 seconds less than FP-growth and Apriori. The accuracy of the PCA-ISSA-BPNN model reached 99.05%, the F1 value was

96.43%, and the recall reached 97.26%. The IApriori algorithm can more efficiently complete the indicator screening work. Moreover, PCA-ISSA-BPNN can effectively achieve intelligent TQE in universities and improve the rationality of teaching evaluation. Nevertheless, since the experimental data used in the study are all from the same university, there may be deviations in the experimental results. Therefore, future research should expand its scope to include multiple institutions to improve the reliability of research results.

Conflict of Interest

The author declares no competing interests.

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