ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Research on the Management of Online Teaching Quality in Vocational Colleges Based on Data Mining Algorithms

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SUMMARY: *To address the current bias and subjectivity in online teaching quality evaluation in higher vocational colleges, this paper proposes an online teaching quality management method based on data mining algorithms. The Apriori algorithm analyzes teaching data, calculates the support and confidence levels of the data, and adaptively determines the threshold using high-order polynomial curve fitting. Next, the paper systematically identifies key factors influencing teaching quality from three dimensions: the teaching platform, teachers, and students. A quantitative indicator system is constructed, including student satisfaction and platform stability. Based on this, an online teaching quality management framework is designed, comprising a driving layer, an action layer, a guarantee layer, and an evaluation layer, supporting functions such as grade processing, entry, and query. Grades are assessed using a parallel grading and percentage system, achieving scientific grading through discretization and critical value division. Experiments show that, with 400MB of teaching resources, this method achieved a support value of 0.22 and a confidence level of 0.72, demonstrating high student usage. After applying this method, the download and usage rate of core course supplementary materials reached 85%, and the success rate of video-assisted learning in practical courses increased from 70% to 88%. In an evaluation of five teachers, this method's error rate was generally lower than that of the comparison method, validating its effectiveness and superiority in accurately assessing teaching quality and supporting management decision-making.*

KEYWORDS: *Data mining algorithm; Apriori algorithm; Higher vocational college; Online teaching quality; Teaching rating*

1 Introduction

The development of information technology and the innovation of educational concepts have made online teaching in higher vocational colleges an important part of education. Its teaching quality affects talent training and social development. At present, the scale of online teaching is expanding. How to scientifically and accurately evaluate its quality and provide a strong basis for teaching management has become a key issue facing higher vocational colleges.

Many scholars have conducted research in the field of teaching quality evaluation. Reference [1] constructed a comprehensive evaluation system for the teaching quality of college teachers. It considers multiple dimensions such as teaching attitude, content, and methods, and relies on expert scoring to determine the weight of indicators for evaluation.

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https://doi.org/10.65102/is2026736
Published: 30 April, 2026

However, this method relies on the subjective judgment of experts. Different experts have different understandings of indicators and scoring standards. The evaluation results are highly subjective and it is difficult to objectively and accurately reflect the actual level of teachers. Reference [2] proposed a preschool teacher teaching quality evaluation model based on deep learning, which uses deep learning algorithms to analyze teaching videos, student feedback and other data for evaluation. Deep learning models require a large amount of high-quality labeled data for training. It is difficult to obtain sufficiently accurate labeled data, and the model has poor interpretability. It is difficult to identify specific problems in teachers' teaching, which is not conducive to teachers' targeted improvement of teaching. Reference [3] uses data mining technology to evaluate the quality of college English teaching. By analyzing data such as students' academic performance and homework completion, factors affecting teaching quality are mined. However, this study only focuses on students' learning results data and ignores teaching process data such as classroom interaction and online learning time. Teaching process data is very important for comprehensively evaluating teachers' teaching level, so the evaluation results are not comprehensive and accurate. Reference [4] uses a fuzzy decision support system to evaluate the quality of college physical education teaching. It considers various fuzzy factors in the teaching process and determines the teaching quality level by establishing a fuzzy evaluation matrix. However, the fuzzy rules and membership functions in the fuzzy decision support system rely on expert experience and are subjective. Moreover, the system has difficulty in processing complex and nonlinear teaching data relationships, which also affects the accurate evaluation of teachers' actual teaching level.

Existing research has achieved results in teaching quality evaluation, but they all have limitations and are difficult to accurately and comprehensively reflect the actual level of teachers in online teaching in higher vocational colleges. Based on this, this paper explores a method for managing online teaching quality in higher vocational colleges based on data mining algorithms, overcoming existing shortcomings and providing scientific support for improving online teaching quality.

2 Fitting a Data Mining Algorithm to an Online Teaching Dataset for Higher Vocational Colleges

In response to the large-scale dataset generated during online teaching in vocational colleges, this study first uses data mining algorithms to conduct fitting analysis, laying a data foundation for the subsequent mining of teaching quality factors. The core work of the mining phase includes selecting suitable data mining algorithms and constructing a complete and operable technical implementation process. This process requires the calculation of key indicators of data correlation (including support and confidence [5, 6]), and the use of high-order polynomial curve fitting methods to adaptively determine their effective thresholds.

Support measures the frequency with which itemsets X and Y co-occur in the online teaching dataset S [7]. Its calculation formula is as follows:

$$Sup(X \Rightarrow Y) = \frac{|X \cup Y|}{|S|} \tag{1}$$

where: $|X \cup Y|$ represents the number of data records containing both itemsets X and Y. $|S|$ represents the total number of records in dataset S.

As a key metric in association rule mining, support reflects the frequency level of a certain set or behavior combination appearing in the entire dataset. In the online teaching scenario of vocational colleges, high support means that a certain type of teaching interaction mode is more common among the student population, and this mode has good representativeness. However, support only focuses on frequency and ignores conditional probability, so it needs to be used in conjunction with confidence to more comprehensively characterize the strength of the correlation between teaching behaviors.

The essence of confidence is a posterior probability, which represents the likelihood of the next event occurring if the previous condition is met. From the perspective of teaching evaluation, rules with high confidence often indicate which teaching behaviors have a significant predictive effect on learning outcomes. Confidence describes the probability that a data record containing itemset X also contains itemset Y. Its calculation formula is:

$$Con(X \Rightarrow Y) = \frac{Sup(X \Rightarrow Y)}{Sup(X)} \tag{2}$$

where: $Sup(X)$ represents the support of item set X.

To accurately determine the effective support and confidence values, a high-order polynomial curve fitting method is used, with the number of fits set to 4. Let the fitting curve function be:

$$f(X) = aCon(X)^4 + bCon(X)^3 + cCon(X)^2 + dCon(X) + e \tag{3}$$

where: $Con(X)$ represents the confidence of item set X. a, b, c, d, e represent the weight coefficient.

Then $f(X)$'s second-order derivative is:

$$F(X) = 12aCon(X)^2 + 6bCon(X) + 2c \tag{4}$$

Let the second-order derivative function $F(X) = 0$, and the confidence corresponding to the obtained $Con(X)$ value is the adaptive minimum confidence [8].

Sort the support and confidence of the discretized online teaching dataset in ascending order, and construct a "rank-value" pair [9] based on the second-order derivative function $F(X)$, automatically obtain support and confidence thresholds that match the characteristics of the online teaching dataset.

3 Determining the Factors Influencing the Quality of Online Teaching in Higher Vocational Colleges

CART algorithm is a decision tree algorithm widely used for data classification and regression analysis [10, 11]. This algorithm adopts a unique binary recursive segmentation technique, which can efficiently process large-scale complex datasets. It improves data processing speed and generation stability by recursively constructing decision trees [12]. In online education data analysis, CART algorithm can accurately mine potential patterns in data and assist vocational colleges in evaluating the quality of online teaching.

To accurately determine the factors influencing the quality of online teaching in higher vocational colleges and provide a scientific basis for teaching improvement, we first need to conduct an in-depth analysis of the relevant influencing factors. This paper analyzes the factors influencing the quality of online teaching in higher vocational colleges from three dimensions: teaching platform, teachers, and students. The specific relationships are shown in Figure 1.

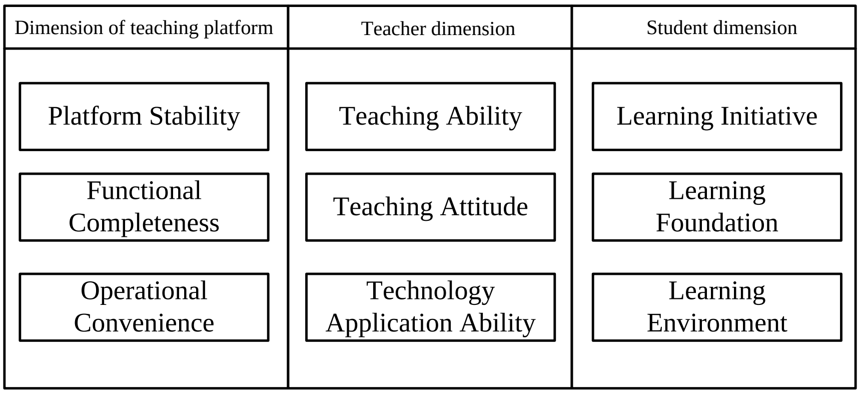

Figure 1: Factors influencing online teaching quality in higher vocational colleges

This influencing factor system is jointly evaluated by teaching platform operations and maintenance personnel, online teaching supervisors, and students. Students, as direct participants in online courses, are the recipients of teaching services [13]. However, their understanding of the principles and specifications of online teaching technology is limited, so their evaluation indicators are designed primarily from the perspective of learning experience and ease of knowledge acquisition. A student online learning satisfaction indicator S is set, calculated as follows:

$$S = \frac{\sum_{i=1}^{n} s_i}{n} \tag{5}$$

where: s_i represents the satisfaction rating of the i-th student towards the online course (out of 10 points), n represents the total number of students participating in the rating.

Online teaching supervisors have sufficient experience, rich professional knowledge, and a deep understanding of online teaching standards. The evaluation indicators focus on professional evaluation of online teaching quality [14]. The operation and maintenance personnel of the teaching platform evaluate the stability of platform functions, the response speed of technical support, and pay more attention to the operational efficiency of the platform. Then, set the platform stability index P, whose formula is:

$$P = \frac{T_z}{T_s} \times 100\% \tag{6}$$

where: T_z represents the time the platform operates normally within a certain period, T_s represents the total duration of that period.

For the convenience of evaluation work, the results of all evaluation indicators are based on a 5-point scale:

Level 1 (Excellent) represents that the evaluation indicators have reached a demonstrative level, and each performance significantly exceeds the established standards;

Level 2 (excellent) indicates good performance in indicators, with occasional shortcomings that do not affect overall effectiveness; Level 3 (good) indicates that the teaching management requirements are basically met, but there are areas for improvement;

Level 4 (qualified) is the minimum acceptable level, which only meets the basic operating conditions;

Level 5 (unqualified) means that the indicators have not met the basic requirements and need to be rectified as a priority.

This five level system draws on the grading idea of Likert scale, transforming qualitative evaluation into ordered discrete variables for subsequent statistical analysis. At the same time, there is a clear progressive relationship between each level, which can intuitively reflect the degree of differences in teaching quality in different dimensions, and also provide a unified evaluation reference for teaching supervisors and platform operation and maintenance personnel.

4 Constructing a Quality Management Framework for Online Teaching in Higher Vocational Colleges

All data related to online teaching is automatically collected from the three dimensions of the teaching platform, teachers, and students. The quality management framework for online teaching in higher vocational colleges should have the following functions:

Administrators from the school's teaching management department will complete special grade processing, such as course grade adjustments due to force majeure [15], inter-semester supplementary exam grade entry, grade verification for students changing majors, and accepting online certification exam registrations and importing certification exam scores.

Each college's teaching secretary can enter the online course grades of all students in that college, or college departments can enter the grades of all online courses taught by that college or department. Online instructors can also enter and submit student grades for their online courses. Student grades can be entered by course, administrative class, or online learning group, and by teaching module, administrative class. Student grades can be entered and submitted via the campus intranet or the internet.

Providing diverse information query channels makes it easy for teachers, students, and administrators to stay informed about online teaching.

Providing multivariate statistical analysis reports [16], such as calculating the total grade point total of all online courses taken by student ID in a specific online teaching cycle, academic year, or since enrollment; calculating the number of students in each grade range for each online course; and calculating the number of online courses taken by students in each grade range based on their administrative class. The online teaching quality management framework for higher vocational colleges is shown in Figure 2.

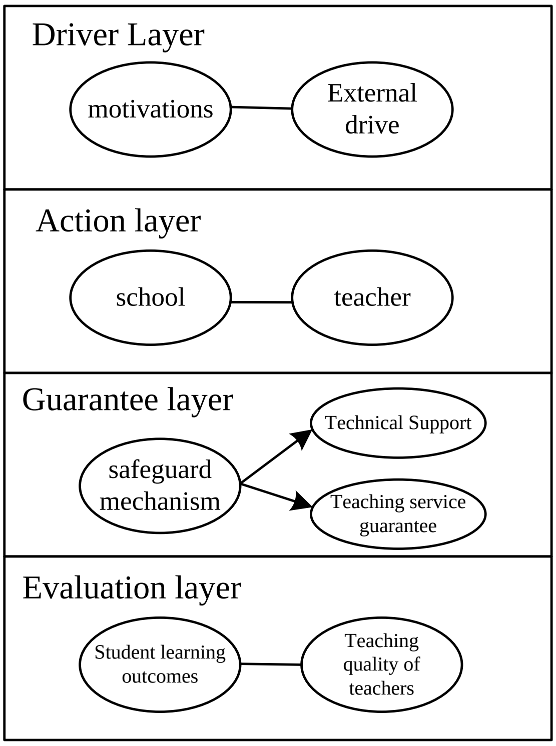

Figure 2: Diagram of the online teaching quality management framework for higher vocational colleges.

1) Driver layer. Improving the quality of online teaching in higher vocational colleges is driven by both internal and external factors. Internal drivers stem from the development needs of schools and teachers, such as schools' desire to enhance their online education brand influence, teachers' pursuit of teaching achievements, career development plans, and a desire for teaching innovation, as well as the need to meet students' diverse learning needs. External drivers stem from policy guidance from education authorities and societal expectations for online education quality. Authorities establish standards and norms, creating external impetus for schools to prioritize and enhance online teaching quality.

2) Action Level. The action level involves specific actions taken by schools and teachers to improve the quality of online teaching. First, schools should integrate high-quality online teaching resources and work with teachers to determine online teaching objectives and content. Subsequently, teachers should innovate teaching methods and approaches based on the characteristics of online teaching, conduct online teaching activities, and promptly interact with students and answer their questions.

3) Guarantee Level. Managing the quality of online teaching is complex, and schools and teachers alone cannot guarantee steady improvement. Therefore, a comprehensive guarantee mechanism [17] must be established, encompassing both technical support and teaching service assurance. The former ensures the stable operation of the online teaching platform, while the latter provides students with comprehensive learning support.

4) Evaluation Layer. The evaluation layer comprehensively assesses the effectiveness of online teaching quality management. It primarily assesses student learning outcomes and teacher teaching quality. By collecting student learning data and teacher feedback, and applying scientific evaluation methods, online teaching quality is objectively and impartially evaluated.

5 Implementing Online Teaching Quality Management Scoring in Higher Vocational Colleges

The online teaching quality management scoring system for higher vocational colleges combines the characteristics of online professional courses with established standards, using both a grading system and a percentage system for grading [18]. Among which

① The hierarchical system is divided into five levels based on the quality management framework: excellent, good, qualified, to be improved, and unqualified. The statistical process prioritizes the use of the hierarchical system for overall comparison and classification summary. The specific classification criteria are: 85 points or above are excellent, 75 points to 84 points are excellent, 60 points to 74 points are qualified, 50 points to 59 points are to be improved, and below 50 points are unqualified. This grading scheme refers to the actual distribution characteristics of the academic level of vocational college students, while taking into account the differentiated requirements of professional courses for knowledge mastery.

② The percentage system is suitable for scenarios that require precise differentiation of student performance differences, such as course rankings, scholarship evaluations, and recommendations for further education. The percentage range is set from 0 to 100, with 100 being the highest score and 60 being the passing line.

The parallel use of the grading system and the percentage system not only retains the advantages of the percentage system in quantitative accuracy, but also simplifies the statistical and decision-making processes in macro management with the help of the grading system. This helps teaching management departments, secondary colleges, and subject teachers to flexibly choose suitable evaluation tools at different levels, and improves the operability and adaptability of online teaching quality management.

In order to more accurately analyze the effectiveness of students' online learning and the quality of teachers' teaching, it is necessary to discretize the overall scores of students' online learning and complete the grading setting in the data preprocessing stage. The grade levels are divided into five levels. After statistical analysis of the grade data of multiple online courses, it is found that the distribution of course grades generally presents normal distribution characteristics , and its standard deviation coefficient is between 0.38 and 1.15.

Assuming that the average score of online course grades is represented by Q and the standard deviation is represented by B_Q. In order to scientifically classify grades, the following interrelated complex mathematical formulas can be constructed. Equation (7) is used to determine the critical value for grading grades, and grades are divided into different intervals based on standard deviation:

$$\begin{cases} Q_1 = Q + 1.15B_Q \\ Q_2 = Q + 0.38B_Q \\ Q_3 = Q - 0.38B_Q \\ Q_4 = Q - 1.15B_Q \end{cases} \tag{7}$$

where: Q_1, Q_2, Q_3 and Q_4 respectively represent the critical grade values of the grade [19, 20].

According to the student's actual score Q', the grade to which it belongs can be determined, which is achieved through the following logical judgment:

If $Q' \geq Q_1$, the student's grade is excellent; If $Q_2 \leq Q' < Q_1$, the student's grade is good; If $Q_3 \leq Q' < Q_2$, the student's grade is qualified; If $Q_4 \leq Q' < Q_3$, the student's grade is to be improved; if $Q' < Q_4$, the student's grade is unqualified.

Through formula (7) and the corresponding grade classification logic, the online teaching quality of higher vocational colleges can be scored and managed more scientifically and objectively, providing a strong basis for teaching improvement.

6 Experiment and Analysis

6.1 Experimental Environment

The experimental environment consists of two major components: hardware and software, as shown in Figure 3. This supports research on online teaching quality management in higher vocational colleges based on data mining algorithms. Regarding hardware, the system is equipped with an AMD Ryzen 9 processor, offering powerful multi-core processing capabilities and efficient handling of complex computations. It also has 32GB of RAM, ensuring smooth system operation when processing large amounts of data. A 1TB SSD provides fast read and write speeds, accelerating data loading and storage, and ensuring efficient processing and analysis.

Regarding the software environment, the Ubuntu 22.04 operating system was selected, providing a stable and secure foundation for research. The PostgreSQL 14 database management system efficiently stores and manages massive amounts of online teaching data and supports complex queries. Python 3.10 is used for data processing and analysis, with its rich libraries and frameworks facilitating algorithm implementation. Libraries such as SciPy and the XGBoost tool were also introduced to meet diverse data mining needs.

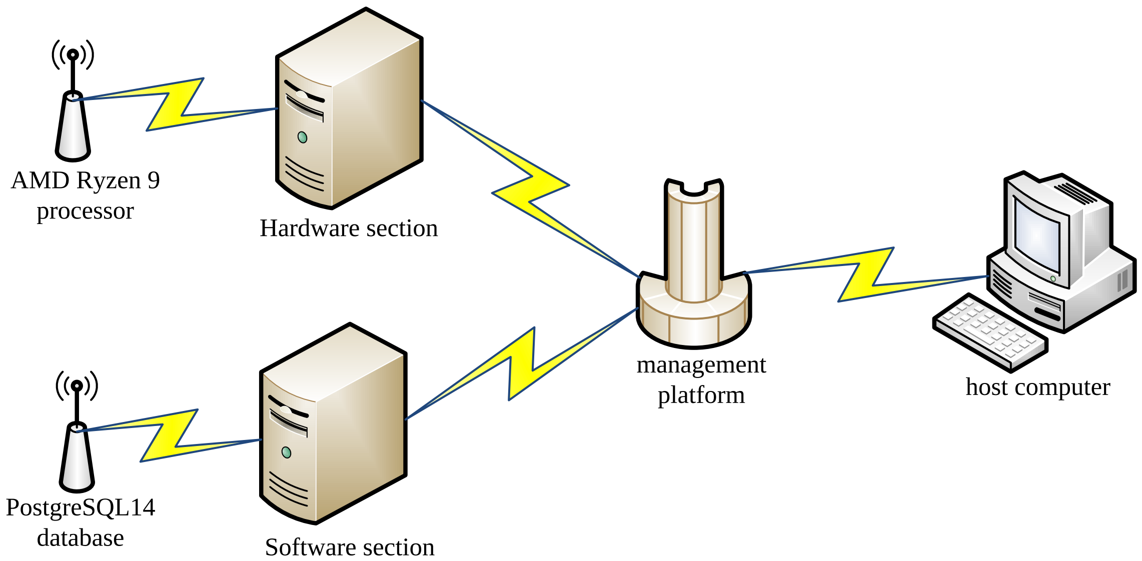

Figure 3: Experimental Environment

During the experiment, the key parameters of the data mining algorithm were carefully set, as shown in Table 1.

Table 1: Key Parameters of the Data Mining Algorithm

Data Mining Algorithm	Key Parameter Name	Parameter Setting Value
Decision Tree Algorithm (CART)	Minimum Split Samples	20
Decision Tree Algorithm (CART)	Maximum Tree Depth	8
Support Vector Machine Algorithm (SVM)	Kernel Function Type	RBF (Radial Basis Function)
Support Vector Machine Algorithm (SVM)	Penalty Coefficient	1.5
Neural Network Algorithm (BPNN)	Number of Hidden Layer Neurons	50
Neural Network Algorithm (BPNN)	Learning Rate	0.01
K - Means Clustering Algorithm	Number of Clusters	4
K - Means Clustering Algorithm	Maximum Number of Iterations	300

In data preprocessing, Word2Vec was used to vectorize text-based teaching feedback data, with the vector dimension set to 200 to represent semantic meaning. With these parameter settings, the performance of processing online teaching data was evaluated to ensure the practical and reliable results.

6.2 Experimental Preparation

Data were collected from higher vocational colleges for the online teaching quality management experiment based on the data mining algorithm. The collected data includes multiple dimensions, including course number, title, instructor number, total class hours, number of students enrolled, student grades, resource uploads, and number of teacher-student interactions. See Table 2 for details, providing a data foundation for the experiment.

Table 2: Data Structure for Online Teaching Quality Management

Course Code	Course Name	Instructor ID	Total Class Hours	Number of Student Enrollments	Average Student Grade	Number of Course Resources Uploaded
C001	Advanced Mathematics	T001	64	120	78.5	35
C002	College English	T002	72	150	82.3	40
C003	Computer Fundamentals	T003	48	90	75.6	28
C004	Mechanical Drawing	T004	56	110	80.1	32
C005	Introduction to E - commerce	T005	40	85	73.2	25

"Practical Core Teachers" refer to teachers who possess both solid teaching skills and extensive experience in enterprise practical projects and have obtained authoritative industry certifications. From the comprehensive teaching database of institutions, we accurately extract details of these teachers' practical project participation over the past four years, including project type, duration, training duration, online competition wins for students they mentored over the past two years, and teaching evaluation scores over the past five years, as shown in Table 3.

Table 3: Details of "Practical Core Teachers'" Participation in Practical Projects over the Past Four Years

Instructor ID	Types of Practical Projects (Last 4 Years)	Project duration (Months)	Training duration (Hours)	Awards for Guiding Students in Online Competitions (Last 2 Years)	Teaching Evaluation Scores in the Last 5 Years
T001	Software development projects	18	48	One second prize in provincial online competitions, Two first prizes in school-level online competitions	88, 90, 92, 91, 93
T002	Debugging of industrial robots	20	52	One third prize in national online competitions, One first prize in provincial online competitions	90, 91, 93, 92, 94
T003	E-commerce platform operation	16	40	Two second prizes in provincial online competitions	86, 88, 90, 89, 91
T004	Architectural engineering design	22	56	One second prize in national online competitions	92, 93, 95, 94, 96
T005	Debugging of automotive electronic control systems	14	36	Three first prizes in school-level online competitions	85, 87, 89, 88, 90

In experimental preparation, the relevant teacher data requires in-depth processing. First, teachers' teaching experience is calculated based on their date of employment and divided into four groups: a[1, 5], b[6, 10], c[11, 15], and d[15 or more]. Next, the teachers' online teaching workload over the past three years is accumulated and averaged, and divided into two groups: W1[0, 120] and W2[120 or more hours]. Finally, the teaching evaluation scores of the past three years were accumulated and averaged, and the students were grouped into groups with good teaching effect (great [85, 100]), good teaching effect (nice [70, 84]), and not so good teaching effect (standard [0, 69]), providing accurate data support for subsequent research.

6.3 Experimental Results Analysis

Verify the strength of correlation between different online learning resource usage behaviors. After collecting massive amounts of online learning data, we apply data mining algorithms to calculate the support and confidence levels for the combined use of various resource types. Combining these two key indicators, we derived the correlation between online learning resource usage patterns, with the relevant data presented in Figure 4.

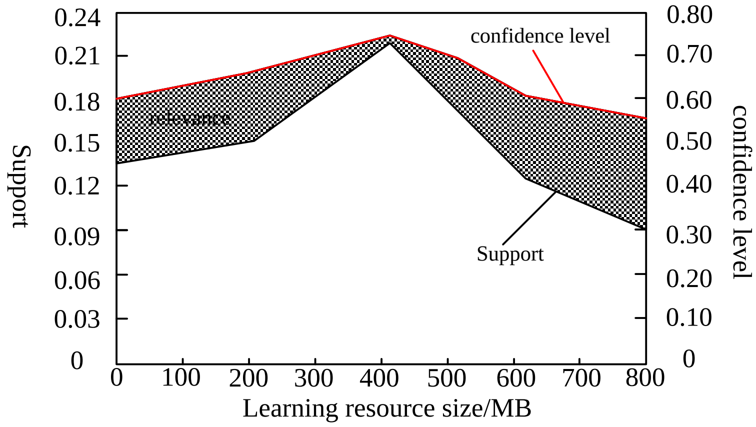

Figure 4: Correlation between online learning resource usage behavior patterns

From Figure 4, it can be seen that when the learning resource is 400MB, the support is 0.22 and the confidence is 0.72, showing excellent performance in various resource sizes. This indicates that when teachers recommend resources of this size, students use them frequently and with a high probability, demonstrating strong teacher selection and guidance capabilities. However, the 800MB resource has a lower support score of 0.09 and a confidence score of 0.55, indicating that when teachers recommend large resources, students lack both willingness and ability to use them, and that teachers fail to fully consider their actual needs. Combining the support and confidence scores for different resource sizes clearly demonstrates the correlation between teacher resource recommendations and student learning behavior. This method can be used to accurately assess teacher teaching proficiency, providing strong support for improving teaching quality.

To further validate the effectiveness of the proposed method in terms of the adaptability of teaching resource recommendations, we applied this method to evaluate resource recommendations, with the final results shown in Figure 5.

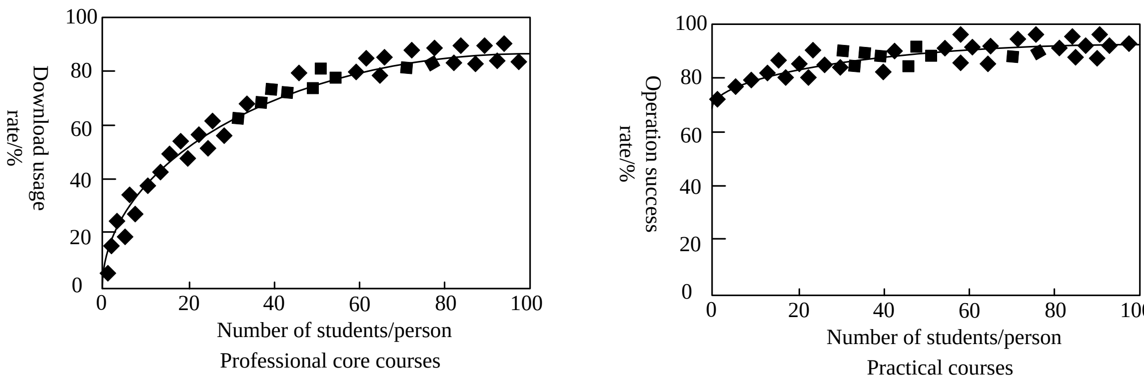

Figure 5: Adaptability of teaching resource recommendations by this method

According to Figure 5, for the core courses of the major, the recommended extension materials in this article have a download and usage rate of 85% among students, and the accuracy of mastering knowledge points related to homework has also been improved. This indicates that the method accurately grasps the teaching needs of teachers, the recommended resources can assist students in understanding, and the teacher's explanation and recommendation ideas are clear and reasonable. For practical courses, the recommended instructional videos based on the method described in this article have increased the success rate of students' practical operations from 70% to 88%, indicating that the recommended resources are in line with the requirements of practical teaching and help students master skills. Overall, the method proposed in this article performs well in terms of the adaptability of teaching resource recommendations, accurately reflecting the teaching level of teachers and providing strong support for improving teaching quality. This is thanks to the method proposed in this article, which constructs a systematic quality influencing factor system from three dimensions: teaching platform, teachers, and students. On this basis, the synergy between the action layer and the assurance layer in the quality management framework enables resource recommendations to reflect both teachers' grasp of knowledge points and students' operational learning needs, thus significantly improving the fit between resources and actual teaching processes.

On this basis, the teaching quality evaluation model constructed in references [1-4] will be compared and validated simultaneously with the method proposed in this paper. To carry out the evaluation work, the selected models are used to evaluate the teaching quality of the five teachers in Table 3, and the error rate of the teaching quality evaluation is calculated. The relevant data is presented in Figure 6.

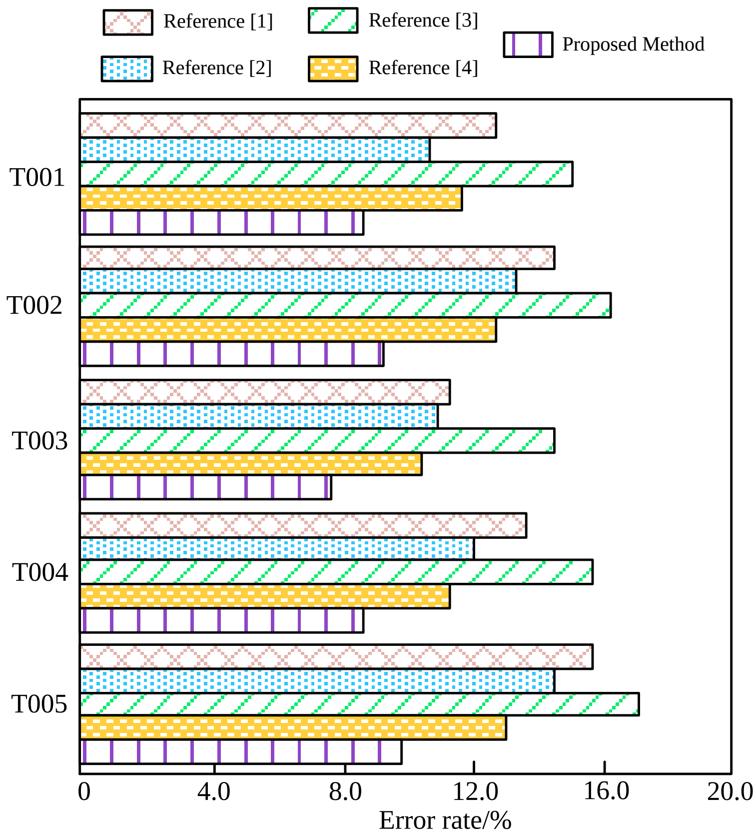

Figure 6: Error rate of teaching quality evaluation

From Figure 6, it can be seen that the error rates of different methods vary. Taking Teacher T001 as an example, the error rates of references [1-4] are 12.5%, 10.2%, 15.0%, and 11.8%, respectively, while the error rate of our method is only 8.5%. Overall, when evaluating 5 teachers, the error rate of the method in this article is generally lower than that of the comparative scheme. This indicates that the evaluation method in this article is more accurate and reliable, and can accurately reflect the teaching level of teachers. This is because the method proposed in this article no longer relies on subjective scores from experts or fuzzy membership settings, but is based on quantitative analysis of the support and confidence levels of actual teaching data. In the process of grading, a parallel system of grades and percentages is adopted, and scientific grading is achieved through discretization and critical value division, reducing the bias caused by human judgment and thus improving the objectivity and stability of the evaluation results.

7 Conclusion

This study proposes a quality management method based on data mining algorithms to address the issues of one sidedness and subjectivity in the evaluation of online teaching quality in vocational colleges. This study combines Apriori association rule mining with high-order polynomial curve fitting to adaptively determine support and confidence thresholds, avoiding interference from fixed thresholds or expert experience in rule extraction; A quantitative indicator system including satisfaction and stability has been constructed from three dimensions: teaching platform, teachers, and students. In the process of performance evaluation, a parallel mechanism of grading and percentage system is adopted, and scientific grading is achieved through discretization and critical value division. The experiment also verified the advantages of this method in terms of resource recommendation adaptability and evaluation accuracy.

However, this method also has certain limitations. The quality of data collected by this method highly depends on the completeness and standardization of the existing teaching management system in the university. If the data is missing or the labeling is inconsistent, it will affect the reliability of the mining results. Moreover, the current analysis is mainly based on structured data, and the utilization of unstructured content such as teaching videos and classroom discussions is not yet sufficient. In addition, the Apriori algorithm has a high computational cost when processing massive amounts of data, and its real-time performance needs to be improved. Therefore, future research will explore multimodal data fusion paths, introduce natural language processing and graph neural network technologies, and explore deep information in text feedback and knowledge graphs; Simultaneously attempt to improve algorithm efficiency or adopt distributed computing frameworks to meet the real-time analysis needs of large-scale online teaching scenarios, and promote the development of intelligent and refined online teaching quality management in vocational colleges.

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