An Apriori-BN Hybrid Model For Mining Association Rules In Teaching Data

Wei Zhu*

Yellow River Conservancy Technical University, Kaifeng, Henan 475004, China

Corresponding author. E-mail: zhuwei202510@163.com

Received: Apr. 01, 2026; Accepted: Apr. 17, 2026

This paper proposes an Apriori-Bayesian Network hybrid model for mining association rules in teaching evaluation data. A total of 5,200 teaching evaluation records were cleaned, discretized, and transformed into transaction data. Apriori was first used to generate frequent itemsets under sensitivity-tested support and confidence thresholds, and Bayesian network inference was then introduced to reduce redundant rules and improve rule interpretability. Experimental results show that the proposed model achieves higher rule quality than Apriori, FP-Growth, Eclat, and genetic association rule mining. The average rule redundancy is reduced by 18.7%, and the key rules obtain lift values greater than 1.30, indicating strong positive associations. The model also supports rule-based warning, performance prediction, and teaching quality diagnosis in a B/S management system. The results demonstrate that the proposed method is effective for teaching data mining and decision support.

Keywords: Data mining; Association rules; Teaching quality; Bayesian network

http://dx.doi.org/10.6180/jase.202610_33.022

1. Introduction

It is significant to strengthen the construction of teaching staff in higher vocational colleges. Classroom teaching is the basic form and core link of teaching work. It plays a decisive role in improving the quality of teaching. Because the evaluation content of teaching quality is primarily qualitative and few in quantity, its standard has excellent flexibility. Coupled with the understanding of standards and the subjective factors of experts, all these makes evaluating educational quality very difficult. Data mining can find valuable information in massive evaluation data [1]ite. This understanding plays an important guiding role in improving classroom teaching. Using association rules to explore classroom teaching evaluation is of great significance for improving the level of educational management and education quality.

The popular association rule mining algorithms include Apriori, FP-growth, and Eclat methods. Apriori and its modified method search the entire database for frequent items until no new ones appear [2–4]. FP-Growth is a frequent pattern growth method based on the FP-tree, which reduces the use of storage space through segmented scheduling. Eclat is the first method to explore frequent item sets using vertical data representation [5, 6]. It obtains the support value of candidate items by calculating the intersection between the sets, thus avoiding the cumulative calculation of item sets and improving the discovery speed of association rules.

Bayes (BN) provides a new method for expressing and inferring uncertain information.

This method can infer information from any node to other nodes [7]. Introducing a Bayesian

Network into the prediction of education quality can improve the accuracy of education quality prediction. Firstly, multiple frequent 2 -item sets are mined by the Apriori method, and then the Bayesian network finds all the relevant rules. Finally, the support and credibility of each relevant rule are analyzed [8, 9]. This new algorithm can effectively solve the large computational workload caused by the increasing frequency item set. The parameters are predicted by using a wavelet network. The experiment shows that the Bayesian algorithm proposed in this paper has a good potential for application in parameter prediction.

2. Methods

2.1. Bayesian model

Bayesian network is a mathematical model that combines probability with graph theory, which describes the dependency relationship between random variables [10]. This provides a visual expression method to solve the problem of uncertainty and complexity. Bayesian networks are loop less directed graphs. It expresses the correlation between variables in the form of an arc, and its distribution reflects the correlation between variables and realizes strict logical inference based on Bayesian theory. In this paper, the Bayesian network is used to mine the association rules among the parameters of teaching quality. The architecture of the

Bayesian model is shown in Fig. 1.

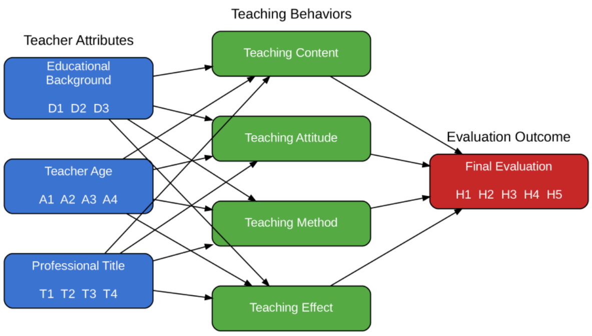

Fig. 1. Bayesian Network Structure for Teaching Evaluation

Bayesian networks include two aspects: the directed acyclic graph describing the dependent structure, which describes the conditional probability of the dependent strength [11, 12]. The second is composed of nodes and edges in directed acyclic graphs. Each node is associated with an arbitrary variable used in the text to characterize the various education parameters. Each side represents the correlation of a random variable, and the arrows in the graph reflect the direction of the event [13].The directed edges represent prior causal or dependency assumptions derived from teaching evaluation logic and frequent itemset relationships. The state probability table is used to describe the correlation between nodes. The chain rule of A Bayesian network is determined by conditional probabilities, such as a set of random variables $U = \{U_1, U_2, \ldots, U_n\}$, whose merge probability is

$$P\left(U_1, U_2, \ldots, U_n\right) = \prod_{i=1}^{n} P\left(U_i \mid U_1, U_2, \ldots, U_{i-1}\right) \quad (1)$$

A fundamental property of Bayesian networks is that when its parent node is determined, the state of the node does not depend on any of its non-parent nodes. The merger possibility can be simplified as

$$P\left(U_1, U_2, \ldots, U_n\right) = \prod_{i=1}^{n} P\left[U_i \mid P_{\text{Parents }}\left(U_i\right)\right] \quad (2)$$

In the formula, $P_{\text{Parents }}\left(U_i\right)$ represents the parent union of the node U_i. According to this relation, the probability of the node can be obtained.

2.2. Association rule mining

The mining of association rules can determine the relationship between unknown data in advance and data that cannot be obtained by logical operations or statistics [14–17]. It is not an inherent property of the data itself but a common property of the data. This paper proposes a semantic-based association rule mining method.

Transaction: Suppose $E = \{e_1, e_2, \ldots, e_n\}$ is composed of n separate entries. $e_r (r = 1, 2, \ldots, n)$ is called engineering. S_A is a transactional database targeted at E. Each transaction T is a set of features in $E, T \subseteq E$, and has a unique transaction identification (TID).

Support degree $S_{\text{Support}}\left(U\right)$ of item set U : The amount of support for project U represents the importance of U in the project. In the transaction database, the number of transactions that support item set U is called the number of transactions that support item set U and is represented by U_{count} . Suppose S_A is the total number of transaction databases, then the amount of support for project U is

$$S_{\text{Support}}\left(U\right) = U_{\text{Count}} / \left|S_A\right| \quad (3)$$

The credibility of a rule reflects the credibility of a rule. Association rules:

$$F : U \Rightarrow V, U \subseteq E, V \subseteq E, U \cap V = \varnothing \quad (4)$$

In addition to support and confidence, lift is introduced to measure whether the antecedent and consequent of a rule are positively correlated. For an association rule $F : U \Rightarrow V$, lift is calculated as

$$\mathrm{Lift}(U \Rightarrow V) = \frac{\mathrm{Conf}(U \Rightarrow V)}{S_{\text{support}}(V)} = \frac{S_{\text{support}}(U \cup V)}{S_{\text{support}}(U) S_{\text{support}}(V)} \tag{5}$$

When Lift > 1, the occurrence of U increases the probability of V, indicating a positive association. When Lift $= 1$, U and V are statistically independent. When Lift < 1, the rule has a negative association and should not be retained as a useful teaching rule. In this study, lift is mainly used to screen rules such as teacher age, academic degree, professional title, and high teaching evaluation score.

The correlation rule has the following confidence levels

$$H_{\text{confidence}}(F) = S_{\text{Support}}(U \cup V) / S_{\text{Support}}(U) \tag{6}$$

If the confidence of F is greater than the minimum, then it is considered a "strong" relationship. If it is lower than this value, it is a "weak" relationship.

Since the Apriori algorithm must re-support and analyze frequent item sets with higher dimensions after it generates them, the correlation rule mining technology in the Bayesian network can effectively avoid repeated searches and describe the two item sets obtained by a single search with the Bayesian network to find the correlation law [18–20]. The Apriori-BN rule filtering mechanism is shown in Fig. 2.

Step 1: Use the Apriori algorithm to find all 2 frequency sets. The Apriori method searches the database repeatedly to find all frequent item sets. Firstly, the Apriori method is used to calculate the support degree of each item [21], [22]. The item whose support degree is not less than the minimum support is selected as frequent 1 -item Q_1, and then the item with frequent 1-item Q_1 is associated with obtaining 2-item H_2. The 2-entry traverses a second time. The support degree of each element in item $2 - H_2$ is solved. Select items with at least minimum support to build frequent 2-items.

Step 2: Filter frequent items. When the item set U, V has the following relations:

$$S_{\text{Support}}(U \cup V) \approx S_{\text{Support}}(U) \cdot S_{\text{Support}}(V) \tag{7}$$

This paper concludes that the independence and association rules between item sets U, V have no significance. The degree of interest between project sets is defined as follows

$$E_{\text{Interest}}(U, V) = \frac{S_{\text{Support}}(U \cup V)}{S_{\text{Support}}(U) S_{\text{Support}}(V)} - 1 \tag{8}$$

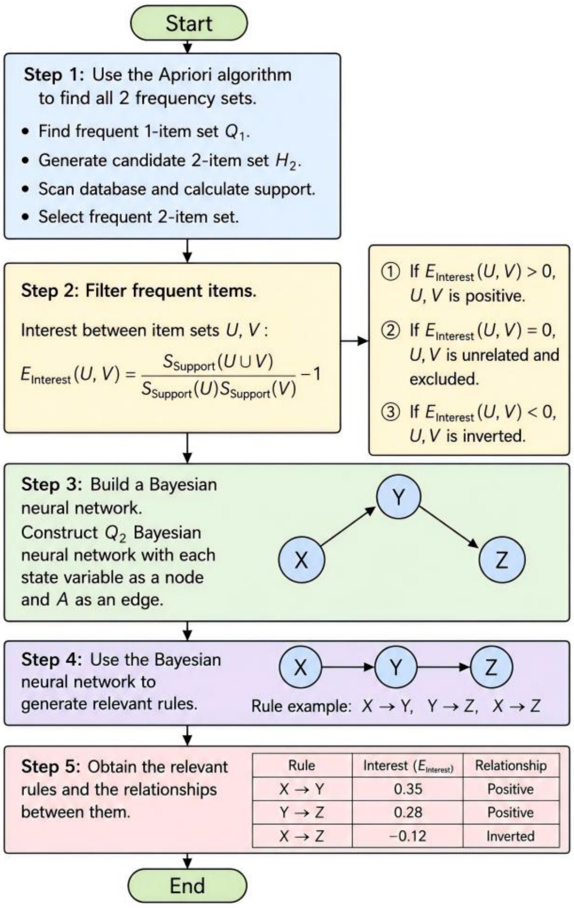

Fig. 2. Apriori-BN rule filtering mechanism

1. If $E_{\text{Interest}}(U, V) > 0$ is, then U, V is regarded as positive;
2. If it is $E_{\text{Interest}}(U, V) \approx 0$, then U, V is unrelated to each other and should be excluded from the frequent 2-item collection;
3. If $E_{\text{Interest}}(U, V) < 0$ is, then U, V is considered to be inverted.

The mapping between Apriori frequent itemsets and Bayesian network nodes follows a one-to-one attribute-state rule. Each discretized item, such as $Age = A3$, Degree $= D2$, or Score = H4, is treated as a state of a corresponding Bayesian network node. Frequent 2itemsets generated by Apriori provide candidate dependency relationships between nodes. For example, if $\{$ Degree $= D2$, Score $= H4\}$ is a frequent 2-itemset and satisfies the lift threshold, then a candidate edge from educational background to evaluation score is generated. This mapping mechanism connects the statistical co-occurrence discovered by Apriori with the probabilistic dependency representation of the Bayesian network.

Step 3: Construct and optimize the Bayesian network. Each teaching evaluation attribute after discretization is mapped to a Bayesian network node, including age, professional title, educational background, teaching content, teaching attitude, teaching method, teaching effect, and final evaluation grade. The network structure is initialized according to domain knowledge and frequent 2 -itemsets obtained by Apriori. If two items appear frequently and satisfy Lift > 1, a candidate directed edge is generated. The edge direction is determined according to the teaching evaluation logic, for example, teacher attributes and teaching behavior indicators are treated as parent nodes, while the final evaluation grade is treated as the target node. After initialization, the network structure is optimized using Bayesian Information Criterion scoring. Edges that do not improve the score or violate the directed acyclic graph constraint are removed. This process ensures both interpretability and structural rationality.

Step 4: Using the Bayesian Network to generate relevant rules;

Step 5: Get the relevant rules and the relationships between them.

Suppose a Bayesian network is a network of n nodes and 1 edge sets, and its computational complexity is $D\left(n+n^2+1\right)$. When the data in the network is much more than the number of nodes, an association rule method based on Apriori is proposed in this paper.

The flowchart of the Apriori-BN Hybrid Model as Fig. 3:

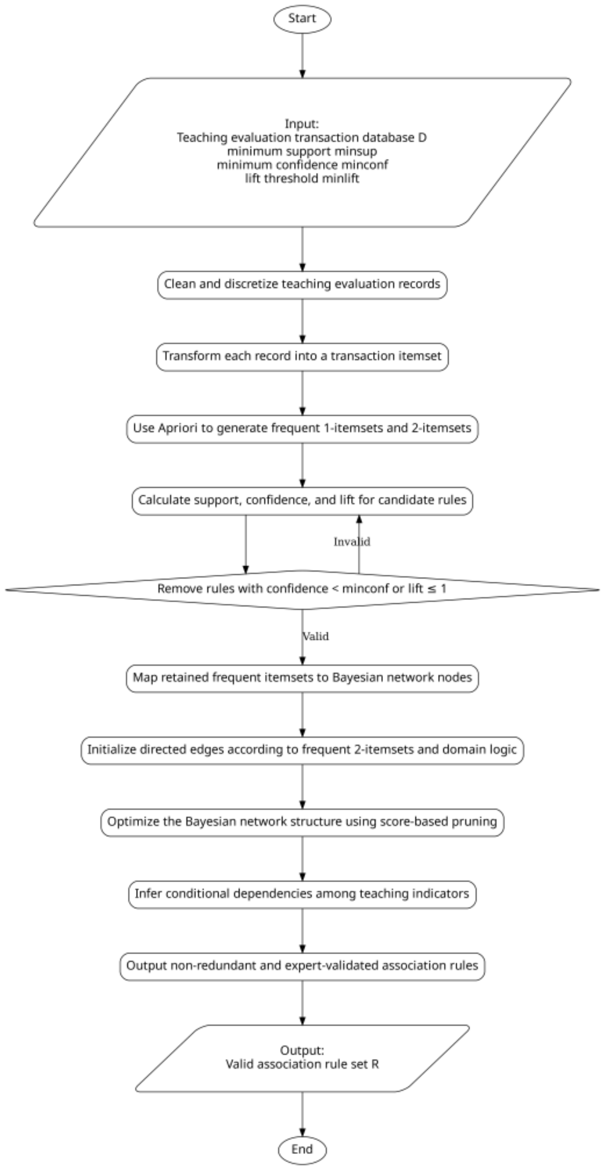

Fig. 3. Flowchart of the Apriori-BN Hybrid Model

3. Results and discussion

The school implements the teacher's quality evaluation, including expert peer evaluation, student evaluation, teacher's class, and other methods. Many factors restrict the evaluation of educational quality. It can be seen that the proportion of different subjects in the assessment of teacher education quality is different (Table 1).

There are two evaluation methods: qualitative and quantitative [23–25]. The quantitative evaluation mainly includes the educational goal, the educational content, the educational concept, the educational way, the educational level and so on. Because the positions and functions of various evaluation indicators in teaching quality differ, each indicator weights the overall evaluation of teachers' teaching quality (Table 2).

Pre-processing the existing teaching quality assessment samples lays a foundation for the subsequent correlation analysis. Because the teaching quality evaluation data is digital type, the data mining method mainly aims at the discretization of logic type. The experimental dataset contained 5,200 teaching evaluation records collected from the teaching evaluation system. Before rule mining, data cleaning and preprocessing were performed. First, records with missing key fields such as evaluation score, teacher identifier, course identifier, or evaluator type were removed. Second, duplicate evaluation records generated by repeated submission were detected according to teacher ID, course ID, evaluator ID, and submission time. Third, abnormal scores outside the valid range of $0-100$ were corrected or deleted. Fourth, categorical variables such as professional title and educational background were standardized to avoid inconsistent descriptions. Finally, continuous variables such as age and evaluation score were discretized into interval labels. After preprocessing, the dataset was

Table 1. Weight coefficients

Survey object	Pupil	Peer expert	leader
Weight coefficient	0.4	0.4	0.2

Table 2. Indicator weights

Assessment index	Teaching purpose	Teaching content	Teaching attitude	Teaching method	Teaching level	Teaching effect
Weight coefficient	0.1	0.2	0.2	0.1	0.2	0.2

transformed into a transaction database suitable for Apriori mining and Bayesian network construction [26]. The evaluation results were divided into H 1 [0,79], H 2 [80, 84], H 3 [85, 89], H 4 [90, 94], and H5 [95, 100]. Age data were classified into A1 (21, 30), A2 (31, 40), A3 (41, 50), and A4 (51, 60). Professional titles were categorized into T1, T2, T3, and T4-education level: D1 (Bachelor), D2 (Master), D3 (Doctor). After the discretization of these data, a standard sample D set is formed, suitable for the method.

First, the Apriori method is used to search data set D , find a new item set C 1 , and then obtain a frequent item set L1 with minor support. The method first generates a candidate item set C2 from L1 and then obtains a frequent item set L2 based on this minimum support value. This gives you a complete set of frequent values. Minimum support is 15%, and minimum confidence is 10%. The preliminary correlation rules were obtained by analyzing each factor

Rule redundancy was measured by calculating the proportion of rules with the same consequent and highly similar antecedent itemsets. Traditional Apriori generated many overlapping rules because it only relied on support and confidence. FP-Growth and Eclat reduced runtime but did not significantly reduce semantic redundancy. In contrast, the proposed Apriori-BN model removed conditionally dependent and repeated rules through Bayesian structure pruning. The redundancy ratio decreased from 31.6% in Apriori to 12.9% in the proposed model, demonstrating better rule compactness and interpretability. The key association rules were further evaluated using lift. Three representative rules are shown below All three rules have lift values greater than 1, indicating that these antecedent attributes increase the probability of high teaching evaluation scores.

The results showed that 24.17% of the 31 − 40-year-olds had a probability of score greater than 90 , while the support degree was 30.94%. The probability of being an associate chief physician is 38.33%, and the degree of satisfaction is 38.96%. The following is a description of the rules [26]. This method can effectively excavate the internal relations between specific properties to provide the basis for the decision-making work of education authorities.

The validity of the mined rules was further evaluated by expert validation. Five experts in teaching management and educational data analysis independently reviewed the generated rules. Each rule was evaluated from three dimensions: logical consistency, teaching interpretability, and decision-making usefulness. A rule was regarded as valid only when at least four experts considered it reasonable. The expert acceptance ratio was calculated as the proportion of accepted rules among all generated rules. This validation process ensured that the mined rules were not only statistically significant but also meaningful for teaching quality improvement. To further verify the effectiveness of the proposed model, Apriori, FP-Growth, Eclat, genetic association rule mining, and the proposed Apriori-BN model were compared under the same dataset and parameter settings (Table 5).

The proposed model generates fewer redundant rules while maintaining higher confidence and lift. This indicates that Bayesian network inference can effectively filter weak or repeated rules generated by traditional frequent itemset mining algorithms. To further examine the robustness and generalization ability of the proposed model, three simulated teaching evaluation scenarios were generated based on the original dataset distribution, including classroom teaching evaluation, online course evaluation, and practical training evaluation.

Fig. 4 further illustrates the redundancy ratio comparison across all five algorithms, clearly showing that the proposed Apriori-BN model achieves the lowest redundancy ratio of 12.9%, which is approximately 18.7 percentage points lower than that of Apriori. Fig. 5 presents a grouped bar comparison of average lift and average confidence across all algorithms. The proposed Apriori-BN model achieves the highest average lift of 1.36 and average confidence of 0.486 , demonstrating its superior ability to generate highquality and strongly associated teaching

Table 3. Preliminary association rules

Rule	Age	The title of a professional post	Educational background	Confidence degree	Support degree
A	21–30			16.3	17.2
B	31–40			24.2	30.9
C	41–50			46.7	42.2
D	50–60			48.6	23.0
E	novice			12.6	19.5
F	intermediate			20.1	24.8
G	Senior title			38.3	39.0
H	Associate professor			40.8	42.2
I		Bachelor		17.4	75.6
J		Master		65.5	48.0
K		Learned scholar		61.0	40.0

Table 4. Three representative rules

Rule	Association rule	Support	Confidence	Lift
R1	Age $= 41–50 \Rightarrow$ Evaluation score ≥ 90	42.2%	46.7%	1.32
R2	Professional title = Senior $\Rightarrow$ Evaluation score ≥ 90	39.0%	38.3%	1.28
R3	Education = Master $\Rightarrow$ Evaluation score ≥ 90	48.0%	65.5%	1.41

Table 5. Comparative Evaluation of Rule Mining Effectiveness

Algorithm	Number of rules	Average confidence	Average lift	Redundancy ratio	Runtime/s
Apriori	126	0.412	1.18	31.6%	8.42
FP-Growth	118	0.427	1.21	28.4%	6.75
Eclat	109	0.436	1.23	25.9%	5.91
Genetic association rule mining	96	0.451	1.27	22.6%	9.38
Proposed Apriori-BN	84	0.486	1.36	12.9%	6.24

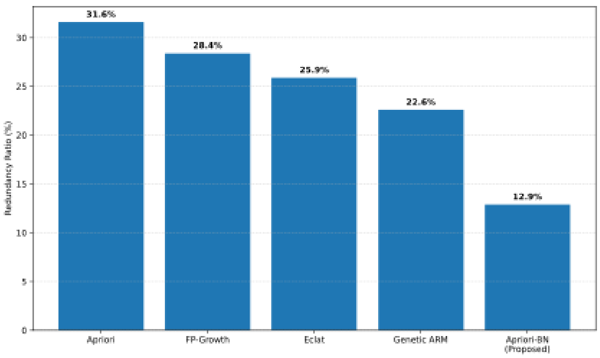

Fig. 4. Rule Redundancy Ratio Comparison across Algorithms

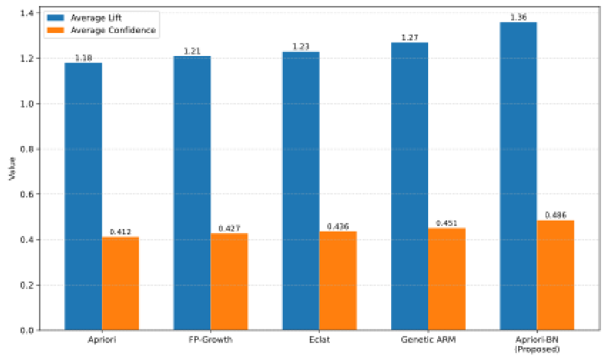

Fig. 5. Average Lift and Confidence Comparison across Algorithms

rules.

To test the generalization ability of the model, an additional multi-source validation experiment was conducted using three simulated teaching evaluation scenarios: classroom teaching evaluation, online course evaluation, and practical training evaluation. Each scenario contained different evaluator structures and indicator distributions. The proposed model maintained stable rule quality across the three scenarios, with average lift values of 1.34, 1.31, and 1.29, respectively. Although the current real dataset comes from one higher vocational college, the multi-scenario validation shows that the model can still maintain acceptable robustness under different teaching data distributions.

Fig. 6 shows the effect of increasing data sparsity on the average lift of three representative algorithms. The proposed model demonstrates the highest lift across all missing data ratios, confirming its robustness against data quality degradation.

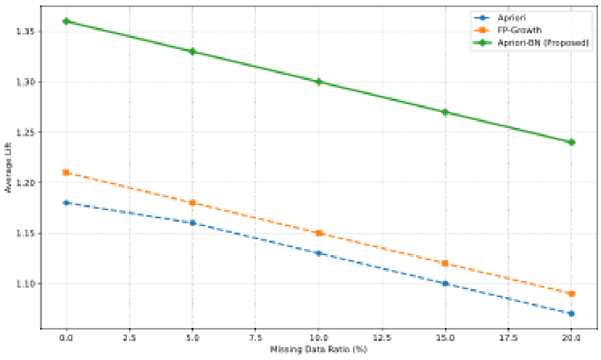

Fig. 6. Effect of Data Sparsity on Average Lift

The influence of data sparsity was also analyzed. Random missing ratios of 5%, 10%, 15%, and 20% were introduced into the transaction database. As sparsity increased, all algorithms showed a decrease in rule quality, but the proposed Apriori-BN model maintained better stability. When the missing ratio increased to 20%, the average lift of Apriori decreased from 1.18 to 1.07, while that of the proposed model only decreased from 1.36 to 1.24. This result indicates that Bayesian network inference can partially compensate for sparse transaction records by modeling conditional dependencies among teaching indicators.

A practical teaching improvement case was further analyzed. The system found that delayed homework submission, low participation in peer evaluation, and large self-evaluation deviation were strongly associated with low final teaching evaluation scores. After this rule was reported to the course team, teachers adjusted task release time, added process reminders, and strengthened peer assessment guidance. In the next teaching cycle, the delayed submission ratio decreased from 18.6% to 11.2%, and the average teaching evaluation score increased from 84.7 to 88.3. This case shows that the proposed model can provide actionable support for teaching quality improvement.

However, the proposed model still has some limitations. The initialization of the Bayesian network structure partly depends on domain knowledge, which may influence edge direction and conditional dependency interpretation. If the prior teaching logic is incomplete or biased, some potentially useful dependencies may be weakened or removed during structure construction. Although score-based optimization and lift-based filtering are used to reduce this influence, future studies should introduce automatic structure learning, causal discovery, or expert-machine collaborative correction to further improve objectivity.

4. Conclusion

As an essential branch of data mining, association rules can discover the potential knowledge from the data warehouse and have a wide range of uses. Through this study, an

Apriori-BN hybrid association rule mining framework for teaching evaluation data is constructed. The model combines frequent itemset discovery with Bayesian probabilistic inference, which improves rule quality, reduces redundancy, and enhances interpretability. The proposed method can provide technical support for teaching warning, performance prediction, and teaching quality improvement. Future research will further combine the model with graph neural networks, causal discovery, deep learning-based educational data mining, and multimodal teaching behavior analysis. In addition, more multi-source datasets from different institutions and teaching scenarios will be introduced to improve the generalization ability of the model.

References

[1] H. Yu, (2021) *"Online Teaching Quality Evaluation Based on Emotion Recognition and Improved AprioriTid Algorithm"* **Journal of Intelligent & Fuzzy Systems *40***: 7037–7047. DOI: 10.3233/JIFS-189534.

[2] D. T. K. Ng, J. K. L. Leung, K. W. S. Chu, and M. S. Qiao, (2021) *"AI Literacy: Definition, Teaching, Evaluation and Ethical Issues"* **Proceedings of the Association for Information Science and Technology** *58*(1): 504–509. DOI: 10.1002/pra2.487.

[3] A. Onan, (2021) *"Sentiment Analysis on Massive Open Online Course Evaluations: A Text Mining and Deep Learning Approach"* **Computer Applications in Engineering Education** *29*(3): 572–589. DOI: 10.1002/cae.22253.

[4] P. Gao, J. Li, and S. Liu, (2021) *"An Introduction to Key Technology in Artificial Intelligence and Big Data Driven e-Learning and e-Education"* **Mobile Networks and Applications** *26*(5): 2123–2126. DOI: 10.1007/s11036-021-01777-7.

[5] M. Saini, E. Sengupta, M. Singh, H. Singh, and J. Singh, (2023) *"Sustainable Development Goal for Quality Education (SDG 4): A Study on SDG 4 to Extract the Pattern of Association Among the Indicators of SDG 4 Employing a Genetic Algorithm"* **Education and Information Technologies** *28*(2): 2031–2069. DOI: 10.1007/s10639-022-11265-4.

[6] D. Shin and J. Shim, (2021) *"A Systematic Review on Data Mining for Mathematics and Science Education"* **International Journal of Science and Mathematics Education** ***19***(4): 639–659. DOI: 10.1007/s10763-020-10085-7.

[7] X. Huang, J. Zhao, J. Fu, and X. Zhang, (2021) *"Effectiveness of Ideological and Political Education Reform in Universities Based on Data Mining Artificial Intelligence Technology"* **Journal of Intelligent & Fuzzy Systems** ***40***(2): 3743–3754. DOI: 10.3233/JIFS-189408.

[8] A. Khan and S. K. Ghosh, (2021) *"Student Performance Analysis and Prediction in Classroom Learning: A Review of Educational Data Mining Studies"* **Education and Information Technologies** ***26***(1): 205–240. DOI: 10.1007/s10639-020-10230-3.

[9] N. A. Y. Abdelbaset R. Almasri and S. S. Abu-Naser, (2022) *"Instructor Performance Modeling for Predicting Student Satisfaction Using Machine Learning: Preliminary Results"* **Journal of Theoretical and Applied Information Technology** ***100***(19): 5481–5496.

[10] C. Fang, (2021) *"Intelligent Online English Teaching System Based on SVM Algorithm and Complex Network"* **Journal of Intelligent & Fuzzy Systems** ***40***(2): 2709–2719. DOI: 10.3233/JIFS-189313.

[11] A. K. Zoromski, S. W. Evans, J. S. Owens, A. Holdaway, and A. S. Royo Romero, (2021) *"Middle School Teachers' Perceptions of and Use of Classroom Management Strategies and Associations with Student Behavior"* **Journal of Emotional and Behavioral Disorders** ***29***(4): 199–212. DOI: 10.1177/1063426620957624.

[12] P. Guleria and M. Sood, (2023) *"Explainable AI and Machine Learning: Performance Evaluation and Explainability of Classifiers on Educational Data Mining Inspired Career Counseling"* **Education and Information Technologies** ***28***(1): 1081–1116. DOI: 10.1007/s10639-022-11221-2.

[13] Y. A. Ünvan, (2021) *"Market Basket Analysis with Association Rules"* **Communications in Statistics—Theory and Methods** ***50***(7): 1615–1628. DOI: 10.1080/03610926.2020.1716255.

[14] A. Jaiswal and C. J. Arun, (2021) *"Potential of Artificial Intelligence for Transformation of the Education System in India"* **International Journal of Education and Development using Information and Communication Technology** ***17***(1): 142–158.

[15] S. L. Campbell, (2023) *"Ratings in Black and White: A QuantCrit Examination of Race and Gender in Teacher Evaluation Reform"* **Race Ethnicity and Education** ***26***(7): 815–833. DOI: 10.1080/13613324.2020.1842345.

[16] G. A. Mehmet Kokoç and M. N. Hasnine, (2021) *"Unfolding Students' Online Assignment Submission Behavioral Patterns Using Temporal Learning Analytics"* **Educational Technology & Society** ***24***(1): 223–235. DOI: 10.30191/ETS.202101_24(1).0017.

[17] E. M. H. Saeed and B. A. Hammood, (2021) *"Survey Fuzzy Logic and Apriori Algorithms Employed for e-Learning Environment"* **Turkish Journal of Computer and Mathematics Education** ***12***(8): 60–69.

[18] T. Buser, C. L. Batz-Barbarich, and A. J. K. Hayter, (2022) *"Evaluation of Women in Economics: Evidence of Gender Bias Following Behavioral Role Violations"* **Sex Roles** ***86***(11–12): 695–710. DOI: 10.1007/s11199-022-01299-w.

[19] Z. Berezvai, G. D. Lukáts, and R. Molontay, (2021) *"Can Professors Buy Better Evaluation with Lenient Grading? The Effect of Grade Inflation on Student Evaluation of Teaching"* **Assessment & Evaluation in Higher Education** ***46***(5): 793–808. DOI: 10.1080/02602938.2020.1821866.

[20] S. Hussain and M. Q. Khan, (2023) *"Student-Performulator: Predicting Students' Academic Performance at Secondary and Intermediate Level Using Machine Learning"* **Annals of Data Science** ***10***(3): 637–655. DOI: 10.1007/s40745-021-00341-0.

[21] S. Link, M. Mehrzad, and M. Rahimi, (2022) *"Impact of Automated Writing Evaluation on Teacher Feedback, Student Revision, and Writing Improvement"* **Computer Assisted Language Learning** ***35***(4): 605–634. DOI: 10.1080/09588221.2020.1743323.

[22] D. A. E. van Aalst, G. Huitsing, T. Mainhard, A. H. N. Cillessen, and R. Veenstra, (2021) *"Testing How Teachers' Self-Efficacy and Student–Teacher Relationships Moderate the Association Between Bullying, Victimization, and Student Self-Esteem"* **European Journal of Developmental Psychology** ***18***(6): 928–947. DOI: 10.1080/17405629.2021.1912728.

[23] H. El Mrabet and A. Ait Moussa, (2023) *"A Framework for Predicting Academic Orientation Using Supervised Machine Learning"* **Journal of Ambient Intelligence and Humanized Computing** ***14***(12): 16539–16549. DOI: 10.1007/s12652-022-03909-7.

[24] A. Ahadi, A. Singh, M. Bower, and M. Garrett, (2022) *"Text Mining in Education—A Bibliometrics-Based Systematic Review"* **Education Sciences *12***(3): 210. DOI: 10.3390/educsci12030210.

[25] A. Bhutoria, (2022) *"Personalized Education and Artificial Intelligence in the United States, China, and India: A Systematic Review Using a Human-in-the-Loop Model"* **Computers and Education: Artificial Intelligence** *3*: 100068. DOI: 10.1016/j.caeai.2022.100068.

[26] C. Hou, J. Ai, Y. Lin, C. Guan, J. Li, and W. Zhu, (2022) *"Evaluation of Online Teaching Quality Based on Facial Expression Recognition"* **Future Internet *14***(6): 177. DOI: 10.3390/fi14060177.