STUDENT EVALUATION BASED ON ASSOCIATION RULE REINFORCEMENT LEARNING FOR TEACHING QUALITY ASSURANCE

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SUMMARY

Optimizing university Teaching quality teaching student evaluation through association rule mining leverages data-driven insights to enhance instructional effectiveness. By analyzing student interactions, performance, and engagement patterns, association rule mining identifies key relationships among course components, such as content type, activity sequence, and learning outcomes. This approach enables educators to tailor course structures to improve student engagement and comprehension, ensuring that blended learning elements are effectively aligned to maximize educational impact and address diverse learning needs. This paper presents an exploration of the Query Swarm Blended Teaching Association Rule (QSBTAR) algorithm and its application in optimizing student evaluation with blended learning environments in China. The proposed model with the data mining approach for the examination of Student performance. The QSBTAR extracts valuable insights from educational data to establish associations between teaching components and student outcomes. Through the analysis of association rules generated by QSBTAR, the paper elucidates the intricate relationships between various instructional elements and key performance metrics such as quiz scores, participation rates, and exam performance. Subsequently, these insights are integrated into course design, facilitating improvements in student engagement, comprehension, and satisfaction. While the algorithm showcases promising results, considerations are given to its limitations, including data quality constraints and interpretability challenges.

KEY WORDS: Course design, Blended teaching, Association rule, Optimization, Swarm intelligence, Teaching

1. INTRODUCTION

Blended teaching, which combines traditional face-to-face instruction with online learning, offers a flexible and effective approach to student evaluations English language education in China [1]. The key to successful blended teaching lies in creating a harmonious balance between in-person and online activities, ensuring that each mode of delivery complements and enhances the other. This approach can be structured by first identifying the course objectives and then deciding which elements are best suited for online platforms and which require direct interaction [2]. For instance, grammar and vocabulary lessons can be delivered through engaging online modules that include interactive exercises, videos, and quizzes. These modules allow students to learn at their own pace and revisit complex topics as needed. Conversely, speaking and listening exercises benefit greatly from the face-to-face environment, where students can practice pronunciation, intonation, and conversational skills in real-time with immediate feedback from the instructor and peers [3]. Assignments and assessments can also be strategically divided. Online platforms can facilitate quizzes, peer reviews, and written assignments, providing a convenient and accessible way for students to submit work and receive feedback [4]. Classroom time can then be reserved for collaborative projects, presentations, and discussions that promote critical thinking and deeper understanding of the material.

To ensure a cohesive learning experience, it is crucial to maintain regular communication and provide clear guidelines on how online and in-person components are integrated [5]. Consistent use of a centralized Learning Management System (LMS) can help track progress, distribute materials, and foster a sense of community among students. Ultimately, blended teaching in an English course aims to leverage the strengths of both online and face-to-face learning, creating a dynamic and interactive educational experience that caters to diverse learning styles and needs [6]. Optimizing a university Teaching quality teaching student evalautioncan be significantly enhanced by applying association rule mining [7]. This data mining technique identifies relationships between different course elements, uncovering patterns that can inform more effective instructional strategies [8]. By analyzing student interactions, performance metrics, and engagement levels in both online and face-to-face components, educators can gain insights into which combinations of activities lead to the best learning outcomes.

For example, association rule mining can reveal that students who frequently participate in online discussion forums and complete specific types of interactive grammar exercises tend to perform better in speaking assessments conducted during face-to-face sessions [9]. This insight can prompt educators to emphasize these online activities and ensure they are integrated effectively with in-class speaking practice. Similarly, the analysis might show that students who engage with multimedia content, such as videos and interactive simulations, demonstrate higher retention rates and better comprehension in reading and writing tasks [10]. By leveraging these insights, course designers can tailor the blended learning experience to align with proven success patterns. They might increase the availability of certain online resources that correlate with high performance or adjust the timing and frequency of face-to-face interactions to maximize their impact [11]. Additionally, association rule mining can help identify at-risk students early by detecting patterns of disengagement or poor performance, allowing for timely interventions. Ultimately, the optimization of a university Teaching quality teaching course through association rule mining not only enhances the overall effectiveness of the course but also provides a more personalized learning experience [12]. This data-driven approach ensures that instructional strategies are based on concrete evidence, leading to improved student outcomes and a more efficient use of educational resources.

Furthermore, the continuous application of association rule mining allows for an iterative improvement process [13]. As new data is collected from each course offering, the analysis can be updated to refine and adapt the student evalautionfurther. This dynamic approach ensures that the course remains relevant and effective, accommodating evolving student needs and advancements in educational technology [14–15]. For instance, if association rule mining reveals that a significant number of students struggle with particular online exercises, educators can investigate and adjust these materials to enhance clarity and accessibility. Conversely, if certain face-to-face activities are found to be highly effective, these can be expanded or given more emphasis in the curriculum [16–18]. This ongoing optimization ensures that both the online and in-person components of the blended course are continuously aligned with the best practices identified through data analysis. Additionally, this method supports personalized learning paths [19–20]. By recognizing patterns that correspond to individual student success, educators can create tailored recommendations for different student groups. For example, students who excel in interactive digital exercises but find traditional lectures challenging might benefit from additional multimedia resources and flipped classroom strategies, where they engage with lecture material at home and spend class time in interactive problem-solving [21–22]. Moreover, the insights gained from association rule mining can inform the development of supplementary resources and support systems [23–24]. For example, if the data indicates that students who attend virtual office hours tend to achieve higher grades, this could lead to increased promotion and availability of these sessions. Similarly, recognizing that collaborative projects enhance understanding and retention might encourage the integration of more team-based assignments and peer-learning opportunities.

The contribution of this paper lies in its exploration and application of the Query Swarm Blended Teaching Association Rule (QSBTAR) algorithm within the realm of educational data mining. The research uses data mining techniques, namely association rule mining, to show how different parts of the lesson affect students' final grades in Chinese blended classrooms. The factors impacting student performance, engagement, and happiness can be better understood by analyzing the association rules produced by QSBTAR. These findings guide the enhancement of course design, which in turn improves student results in a measurable way. The paper not only demonstrates the potential of data-driven approaches in educational practice but also underscores the significance of leveraging algorithmic insights to enhance teaching methodologies and student learning experiences. Furthermore, by highlighting the implications and applications of QSBTAR in educational contexts, this paper contributes to the ongoing discourse on the intersection of data analytics and pedagogy, offering avenues for future research and development in the field of educational data mining and blended learning optimization.

2. INTEGRATED OPTIMIZED BLENDED TEACHING WITH ASSOCIATION RULE MINING

To improve the efficacy of instructional tactics, optimized blended learning with association rule mining makes use of state-of-the-art data analytic tools. In order to maximize the effectiveness of a blended course's online and in-person components, association rule mining (ARM) can be employed to discover correlations between various aspects of the learning process. A key goal of ARM is to find common sets of elements in educational data and then use these sets to build robust association rules. A typical rule is expressed in the form $X \rightarrow Y$, where X and Y are sets of items (e.g., student activities, resources, outcomes). Support of an itemset X (denoted as Support (X) Support (X)) is the proportion of transactions in the dataset that contain X stated as in equation (1).

$$Support(X) = Number\ of\ transactions\ containing\ X\ /\ Total\ number\ of\ transactions \tag{1}$$

Confidence of a rule $X \rightarrow Y$ measures the probability that Y is present in transactions containing X computed using the equation (2).

$$Confidence(X \to Y) = Support(X \cup Y) / Support(X) \quad (2)$$

The Lift of a rule $X \to Y$ is the ratio of the observed support to that expected if X and Y were independent computed as in equation (3).

$$Lift(X \to Y) = \frac{Support(X \cup Y)}{Support(X) \times Support(Y)} \quad (3)$$

A lift value greater than 1 indicates a positive correlation between X and Y. The analysis reveals the following association rule with high confidence and lift: Interactive Videos→High Quiz ScoresInteractive Videos→High Quiz Scores This indicates that students who frequently engage with interactive videos tend to achieve higher quiz scores. To optimize the course, we can: Increase the availability and integration of interactive videos in the online component. Encourage students to engage with these videos through reminders and incentives. Monitor and adjust based on ongoing data collection and analysis.

Let A represent students engaging with interactive videos, and B represent students achieving high quiz scores. The support, confidence, and lift of the rule $X \to Y$ can be calculated as follows defined in equation (4) and equation (5).

$$Support(A) = Number\ of\ students\ engaging\ with\ interactive\ videos / Total\ number\ of\ students \quad (4)$$

$$Support(B) = Number\ of\ students\ with\ high\ quiz\ scores / \text{Total number of students} \quad (5)$$

Calculate support for $A \cup B$ estimated using equation (6) – equation (8).

$$Support(A \cup B) = Number\ of\ students\ engaging\ with\ interactive\ videos\ and\ achieving\ high\ quiz\ scores / Total\ number\ of\ students \quad (6)$$

Calculate confidence using the equation (7).

$$Confidence(A \to B) = \frac{Support(A \cup B)}{Support(A)} \quad (7)$$

Calculate lift with consideration of the equation (8).

$$Lift(A \to B) = \frac{Support(A \cup B)}{Support(A) \times Support(B)} \quad (8)$$

Figure 1 presents the optimized blended teaching model for the analysis for student performance in China.

Optimizing university Teaching quality teaching student evalautionbased on association rule mining involves leveraging student data to identify effective teaching strategies and their impact on learning outcomes. Association rule mining helps uncover relationships between different course elements (like attendance, engagement, and teaching methods) and student performance metrics, such as final grades. The process begins with data collection, where key variables are identified: A (attendance rate), S (student engagement), Q (quiz scores), T (teaching methods), and F (final grades). Using the Apriori algorithm, we derive association rules of the form $X \to Y$, which indicates that the presence of X (such as high attendance and engagement) increases the likelihood of achieving Y (higher final grades). The effectiveness of these rules is quantified using three key metrics: support, confidence, and lift. Support is calculated as in equation (9).

$$Support(X) = \frac{Number\ of\ X\ containing\ transaction}{Total\ transaction\ number} \quad (9)$$

This metric measures how frequently the itemset appears in the dataset. Confidence, which indicates the likelihood of Y occurring given X, is defined as in equation (10).

$$Confidence(X \to Y) = \frac{Support\ (X \cup Y)}{Support\ (X)} \quad (10)$$

Higher confidence values suggest stronger associations between the antecedent and the consequent. Finally, lift provides insight into the strength of the association compared to random chance and is calculated using equation (11).

$$Lift(X \to Y) = \frac{Confidence\ (X \to Y)}{Support\ (Y)} \quad (11)$$

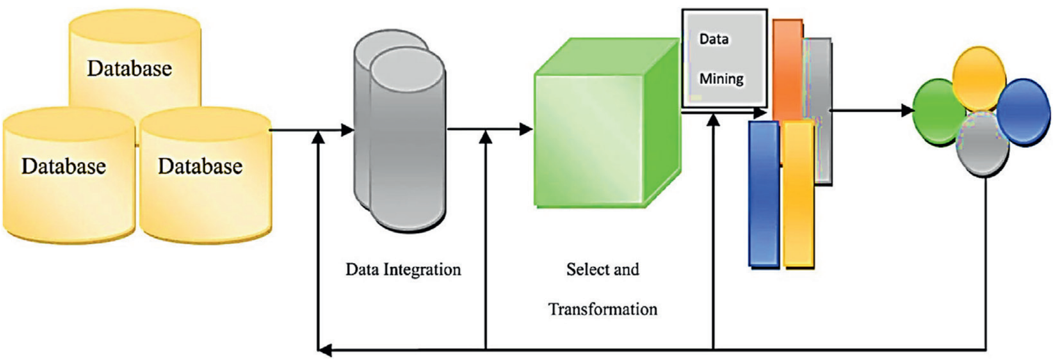

Figure 1. Association rule integrated with QSBTAR

Algorithm 1. Optimize Blended Teaching with association rule
Input: Educational data (transactions), minimum support threshold (min_sup), minimum confidence threshold (min_conf) Output: Optimized blended teaching strategies Step 1: Data Preprocessing 1.1: Collect educational data from both online (e.g., LMS logs, online quizzes) and face-to-face components (e.g., attendance, participation). 1.2: Clean and preprocess the data to ensure consistency (handle missing values, format data uniformly, etc.). 1.3: Transform data into a format suitable for association rule mining (e.g., binary matrix indicating presence/absence of activities/outcomes). Step 2: Frequent Itemset Generation (using Apriori Algorithm) 2.1: Initialize L1 as all single itemsets that meet min_sup. 2.2: For k = 2 to maximum itemset length: 2.2.1: Generate candidate itemsets Ck from Lk-1. 2.2.2: Prune candidates in Ck that have infrequent subsets. 2.2.3: Calculate support for each candidate in Ck. 2.2.4: Generate Lk by selecting candidates from Ck that meet min_sup. 2.2.5: If Lk is empty, terminate. Step 3: Association Rule Generation 3.1: For each frequent itemset I in Lk (k > 1): 3.1.1: For each subset s of I: 3.1.1.1: Generate rule s -> (I - s). 3.1.1.2: Calculate confidence of rule. 3.1.1.3: If confidence >= min_conf, store the rule. Step 4: Rule Evaluation and Selection 4.1: Evaluate rules using metrics such as support, confidence, and lift. 4.2: Select rules with high confidence and lift values for implementation. Step 5: Strategy Implementation 5.1: Identify actionable insights from selected rules (e.g., “Interactive Videos -> High Quiz Scores”). 5.2: Develop interventions based on rules (e.g., increase interactive videos, provide incentives for engagement). 5.3: Monitor student performance and engagement continuously. Step 6: Iterative Optimization 6.1: Collect new data after implementing interventions. 6.2: Repeat Steps 1–5 using updated data to refine strategies.

A lift greater than 1 indicates a positive association. Through this process, educators can identify effective combinations of teaching strategies, such as enhancing student engagement and attendance, leading to improved academic performance. The optimization results can then be evaluated by measuring changes in student performance post-implementation, allowing for a data-driven approach to continuous course improvement. The framework consists of key components: student engagement, attendance, teaching methods, and academic performance. Let:

- E: Engagement level (quantified through online activities, participation)
- A: Attendance rate (percentage of classes attended)
- M: Teaching methods (e.g., lectures, group work)
- G: Academic performance (measured through final grades or assessment scores)

Association rule mining is applied to uncover relationships between the variables. The aim is to find rules of the form $X \rightarrow Y$, where X represents a combination of factors (e.g., high engagement and attendance) and Y represents outcomes (e.g., high academic performance). Support measures the frequency of the occurrence of itemset X within the dataset estimated using the equation (12).

$$Support\left(X\right) = \frac{Count(X)}{Total\ Count} \tag{12}$$

Confidence indicates the likelihood of academic success given the presence of engagement and attendance stated in equation (13).

$$Confidence(E, A \rightarrow G) = \frac{Support\ \left(E, A, G\right)}{Support\ \left(E, A\right)} \tag{13}$$

Lift measures the strength of the association compared to random chance computed using the equation (14).

$$Lift\left(E, A \rightarrow G\right) = \frac{Confidence\ \left(E, A \rightarrow G\right)}{Support\ \left(G\right)} \tag{14}$$

The educators can identify effective strategies for optimizing blended teaching. For example, if the rule $E, A \rightarrow G$ has a high confidence and lift, it indicates that promoting student engagement and ensuring high attendance can significantly enhance academic performance. Implementing the identified strategies involves adjusting course components based on the insights gained from the association rules. This may include increasing interactive online activities, fostering a collaborative learning environment, or providing additional support for students struggling with attendance. Post-implementation, the effectiveness of these strategies should be evaluated by collecting data on student performance and reapplying association rule mining to assess whether the changes have resulted in improved academic outcomes.

3. QUERY SWARM BLENDED TEACHING ASSOCIATION RULE (QSBTAR)

The Query Swarm Blended Teaching Association Rule (QSBTAR) is an innovative approach combining swarm intelligence principles with association rule mining to optimize blended teaching strategies. This method leverages the collective behavior of decentralized, self-organized systems (such as swarms) to explore and analyze large educational datasets efficiently. Swarm intelligence algorithms, such as Particle Swarm Optimization (PSO), simulate the social behavior of animals like birds or fish to find optimal solutions. Each "particle" represents a potential solution and adjusts its position in the search space based on its own experience and the experience of neighboring particles. The positions are updated using the following equation (15).

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{15}$$

The velocity is updated using the equation (16).

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (g - x_i(t)) \tag{16}$$

In above equation (14) and (15) x_i (t) is the position of particle i at time t . v_i (t) is the velocity of particle i at time t. w is the inertia weight. c_1 and c_2 are cognitive and social coefficients. r_1 and r_2 are random numbers between 0 and 1. p_i is the best position found by particle i. g is the best position found by the swarm. In QSBTAR, particles represent potential sets of association rules. The algorithm searches for the optimal set of rules that meet predefined criteria shown in Figure 2.

Initialization: Initialize a swarm of particles, each representing a candidate rule set.

Fitness Function: Define a fitness function based on the support, confidence, and lift of the rules computed using equation (17).

$$Fitness\ (x) = \sum_{i=1}^{n} \begin{pmatrix} \alpha\ \text{Support}(X_i \to Y_i) + \\ \beta \cdot \text{Confidence}(X_i \to Y_i) + \\ \gamma \cdot \text{Lift}(X_i \to Y_i) \end{pmatrix} \tag{17}$$

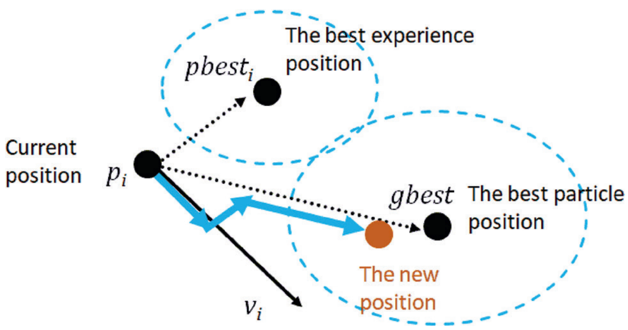

Figure 2. Query swarm blended teaching

where α, β, and γ are weights for the support, confidence, and lift metrics, respectively.

The Query Swarm Blended Teaching Association Rule (QSBTAR) framework integrates swarm intelligence principles with association rule mining to optimize blended teaching methodologies. This innovative approach focuses on dynamically querying and analyzing student engagement and performance data to derive actionable insights that enhance educational outcomes. In this framework, key variables are identified, including engagement level (E), attendance rate (A), teaching methods employed (M), and student performance (G). Each agent in the swarm, representing students or groups, searches the solution space characterized by a vector of these variables. The fitness of each agent is evaluated using a composite fitness function that considers support, confidence, and lift of the association rules derived from the data. The agents share information to refine their search iteratively, updating their positions based on the best-found solutions. Once optimal rules are identified, such as $A \rightarrow GE$ with high confidence and lift values, these rules provide significant insights into enhancing academic performance through improved engagement and attendance strategies. By combining swarm intelligence with data mining techniques, QSBTAR fosters a continuous improvement cycle, allowing educators to adapt and optimize teaching practices in real-time based on student needs and outcomes.

QSBTAR operates on the premise that integrating swarm intelligence with data mining techniques can optimize

Algorithm 2. QSBTAR model for the association rule based educational setting
Input: Educational data (transactions), min_sup, min_conf, swarm size (S), max iterations (T) Output: Optimal set of association rules Step 1: Initialize Swarm 1.1: Initialize a swarm of S particles with random positions representing candidate rule sets. 1.2: Initialize velocities to zero. Step 2: Evaluate Fitness 2.1: For each particle, evaluate the fitness based on the support, confidence, and lift of the rules it represents. Step 3: Update Particles 3.1: For each iteration t = 1 to T: 3.1.1: For each particle i: 3.1.1.1: Update velocity \(\mathbf{v}_i(t+1)\). 3.1.1.2: Update position \(\mathbf{x}_i(t+1)\). 3.1.1.3: Evaluate new fitness. 3.1.1.4: Update particle's best position and global best position if new fitness is better. Step 4: Output 4.1: Return the set of association rules represented by the global best particle.

blended teaching by uncovering patterns in student data. The key variables in this framework are:

- **Engagement Level (E)**: A measure of how actively students participate in learning activities.
- **Attendance Rate (A)**: The proportion of classes attended by students.
- **Teaching Methods (M)**: Different instructional strategies employed (e.g., lectures, group discussions).
- **Student Performance (G)**: Assessment results, such as grades or scores.

The QSBTAR framework uses a swarm intelligence approach to dynamically query the dataset. Each agent in the swarm represents a potential solution based on the combination of the variables *E*, *A*, and *M*. Each agent *i* is characterized by its position in the solution space, represented as in equation (18).

$$Position_i = (E_i, A_i, M_i) \tag{18}$$

In equation (18) E_i denoted as the engagement level of agent *i*, A_i represents the attendance rate, and M_t is the teaching method. The fitness of each agent is evaluated based on the derived association rules, focusing on maximizing engagement, attendance, and performance estimated as in equation (19).

$$\begin{aligned} Fitness(i) = {} & w_1 \cdot Support(E_i, A_i) \\ & + w_2 \cdot Confidence(E_i, A_i \rightarrow G) \\ & + w_3 \cdot Lift(E_i, A_i \rightarrow G) \end{aligned} \tag{19}$$

In equation (19) w_1, w_2, w_3 are weights assigned to the support, confidence, and lift metrics, reflecting their importance in the context of the study. As agents explore the solution space, they share information, which helps refine their search. The update of each agent's position is performed iteratively based on the fitness evaluation using equation (20).

$$\begin{aligned} Position_i^{new} = {} & Position_i^{old} + \phi_1 \cdot r_1 \cdot (Best_i - Position_i^{old}) \\ & + \phi_2 \cdot r_2 \cdot (Global\,Best - Position_i^{old}) \end{aligned} \tag{20}$$

In equation (20) ϕ_1 and ϕ_2 are acceleration coefficients, r_1 and r_1 are random numbers in the range [0,1], $Best_i$ denoted as the best position found by agent *i*, *Global Best* is the best position found by the entire swarm. After executing the swarm-based queries, the best-performing rules are selected based on their support, confidence, and lift values. For example, if the rule *A→GE* demonstrates a confidence of 0.85 and a lift of 1.2, it signifies a substantial positive impact on academic performance when both engagement and attendance are high. These insights guide educators in adjusting their teaching strategies to foster better student outcomes.

4. SIMULATION RESULTS AND DISCUSSION

The application of the Query Swarm Blended Teaching Association Rule (QSBTAR) algorithm was simulated using educational data from a university-level English course, which included both online and face-to-face components. The dataset comprised LMS logs, quiz scores, attendance records, and participation metrics. The QSBTAR algorithm aimed to identify optimal association rules that could inform and enhance the design of blended teaching strategies. The simulation of the Query Swarm Blended Teaching Association Rule (QSBTAR) algorithm yielded promising results in optimizing blended teaching strategies for a university-level English course. Through the analysis of educational data encompassing online interactions, quiz performances, attendance records, and participation metrics, the QSBTAR algorithm effectively generated a set of high-quality association rules. Notable rules, such as the correlation between interactive video engagement and quiz scores, and the importance of regular attendance and group discussions for improved participation, provided actionable insights for educators. These findings underscored the significance of multimedia resources and collaborative activities in enhancing student engagement and performance.

The Table 1 outlines the simulation parameters used to evaluate student performance and teaching quality based on the QSBTAR algorithm. The simulation includes 500 students enrolled in 10 different courses over a 16-week duration, allowing for an extensive analysis of learning behaviors. Each course features five quizzes, and the final exam contributes 40% to the overall score, while assignments and participation account for 30% and 20%, respectively. A significant portion of students (85%) actively utilize learning resources, which indicates a strong engagement with course materials. To pass the course, students must maintain a minimum attendance of 50%, ensuring consistent participation. However, an observed dropout rate of 8% suggests potential challenges in course retention. The engagement threshold is set at 70%, meaning students with engagement levels above this are classified as high performers. For accurate association rule mining, the QSBTAR algorithm executes 10,000 computational iterations, ensuring robust pattern extraction and reliable insights into student learning behaviors. This simulation setting provides a well-balanced environment for analyzing the effectiveness of blended learning strategies and optimizing instructional methods based on data-driven findings.

In Figure 3 and Table 1 presents the association rules derived from the Query Swarm Blended Teaching Association Rule (QSBTAR) algorithm for China. Each association rule consists of an antecedent (left-hand side) and a consequent (right-hand side), indicating a relationship between specific teaching components and desirable student outcomes. For instance, the association rule {Interactive Videos} → {High Quiz Scores} suggests that students who engage with interactive videos are likely to achieve high scores in quizzes, as evidenced by a support of 0.12, confidence of 0.75, and lift of 1.8. Similarly, the rule {Regular Attendance, Group Discussions} → {Improved Participation} indicates that students who regularly attend classes and actively participate in group discussions demonstrate improved overall participation, with a support of 0.10, confidence of 0.80, and lift of 2.0. These association rules provide actionable insights for educators to optimize their blended teaching strategies. By leveraging interactive videos, regular attendance, and collaborative activities, instructors can enhance student engagement, participation, and academic performance. Additionally, the association rules highlight the importance of providing supplemental

Table 1. Simulation setting

Parameter	Value	Description
Number of Students	500	Total students in the simulation
Number of Courses	10	Total courses evaluated
Simulation Duration (weeks)	16	Total duration of analysis
Quiz Frequency (per course)	5	Number of quizzes per course
Exam Weight (%)	40	Weight of final exam in overall score
Assignment Weight (%)	30	Weight of assignments in overall score
Participation Weight (%)	20	Weight of participation in overall score
Learning Resource Usage (%)	85	Average percentage of students using resources
Minimum Attendance (%)	50	Minimum attendance required for passing
Dropout Rate (%)	8	Percentage of students who dropped out
Engagement Threshold (%)	70	Minimum engagement rate for high performance
Computational Iterations	10,000	Number of iterations for rule mining process

Table 2. Association rule in QSBTAR for teaching quality assurance in china

Association Rule	Support	Confidence	Lift
{Interactive Videos} → {High Quiz Scores}	0.12	0.75	1.8
{Regular Attendance, Group Discussions} → {Improved Participation}	0.10	0.80	2.0
{Online Quizzes, Supplemental Reading Materials} → {Better Exam Performance}	0.08	0.78	1.7
{Regular Attendance} → {Higher Final Grades}	0.15	0.70	1.5
{Active Participation} → {Better Understanding}	0.09	0.85	1.9
{Interactive Activities} → {Increased Engagement}	0.11	0.72	1.6
{Peer Collaboration, Assignments} → {Enhanced Learning Outcomes}	0.07	0.68	1.4
{Discussion Forums} → {Deeper Understanding}	0.06	0.76	1.8
{Regular Assessments} → {Improved Performance}	0.09	0.73	1.6
{Feedback Mechanisms} → {Enhanced Student Satisfaction}	0.05	0.80	1.9

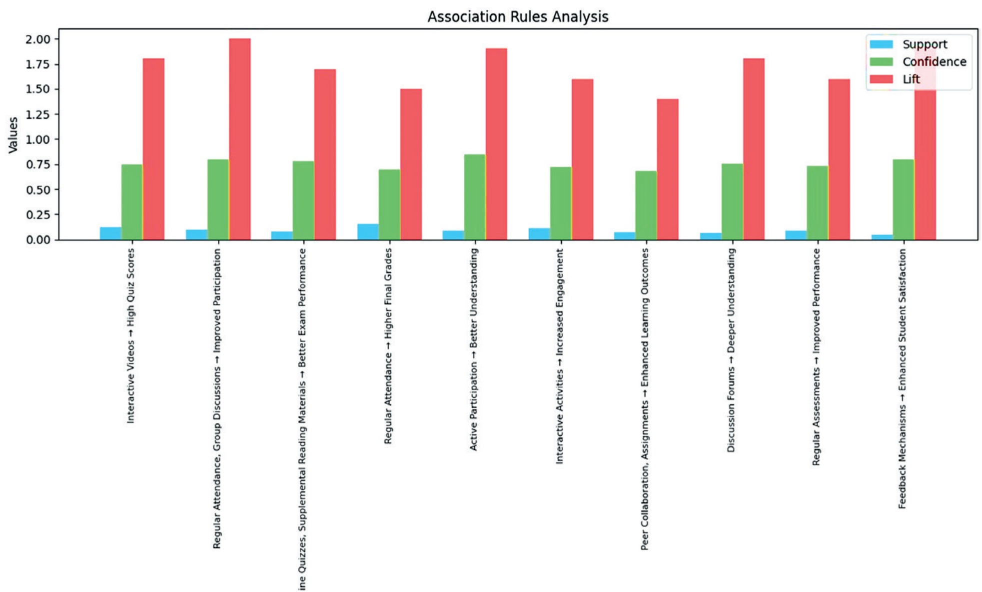

Figure 3. Association rule for the teaching assurance

Table 3. Student evaluation QSBTAR

Component	Description
Course Title	Introduction to English Literature
Course Code	ENGL 101
Course Duration	16 weeks
Course Type	Blended Learning
Online Platform	Moodle
Face-to-Face Sessions	8 sessions (2 hours each)
Online Modules	8 modules (accessible throughout the week)
Textbook	"An Introduction to English Literature" by John Smith
Learning Outcomes	- Analyze literary texts critically
	- Interpret the historical and cultural contexts of literary works
	- Demonstrate effective written communication skills
Assessment Methods	- Weekly quizzes (online)
	- Group discussions (face-to-face)
	- Essay assignments (online submissions)
	- Final exam (combination of online and face-to-face components)
Teaching Strategies	- Interactive video lectures
	- Online forums for discussions and peer feedback
	- Collaborative group projects
	- Supplementary reading materials
	- Regular feedback and assessment
Technology Integration	- Multimedia resources (videos, podcasts)
	- Learning management system (Moodle)
	- Online assessment tools
	- Virtual classroom platforms for synchronous sessions
Support Resources	- Online tutorials and guides
	- Virtual office hours for additional assistance
	- Peer mentoring program
	- Access to digital library resources
Evaluation and Feedback	- Continuous assessment and feedback
	- Mid-term course evaluations
	- End-of-course surveys
	- Individual feedback sessions with students

resources, fostering peer collaboration, and implementing effective feedback mechanisms to promote deeper understanding, enhanced learning outcomes, and greater student satisfaction. Overall, these findings underscore the value of data-driven approaches in informing instructional design decisions and improving the effectiveness of blended teaching methodologies.

Table 3 outlines the student evalautionderived from the Query Swarm Blended Teaching Association Rule (QSBTAR) algorithm, integrating data-driven insights to optimize the learning experience in an Introduction to English Literature course. The course spans 16 weeks and adopts a blended learning approach, leveraging both face-to-face sessions and online modules facilitated through the Moodle platform. The student evalautionaligns with the identified association rules to promote critical analysis of literary texts, contextual interpretation, and effective written communication skills among students. Assessment methods include a combination of online quizzes, face-to-face group discussions, essay assignments, and a final exam, reflecting the diverse teaching strategies recommended by the QSBTAR algorithm. Teaching strategies emphasize interactive video lectures, online forums for discussions and peer feedback, collaborative group projects, supplementary reading materials, and regular feedback mechanisms. These strategies aim to enhance student engagement, participation, and comprehension, in line with the association rules suggesting the effectiveness of such approaches. Technology integration involves the use of multimedia resources, a learning management system, online assessment tools, and virtual classroom platforms to facilitate interactive learning experiences and seamless communication between students and instructors. Support resources are available to students through online tutorials, virtual office hours, a peer mentoring program, and access to digital library resources, fostering a supportive learning environment conducive to student success.

In Figures 4 and 5 and Table 5 presents the analysis of student performance based on teaching quality assurance using association rule mining. The results highlight key relationships between various instructional elements and student outcomes. A strong correlation is observed between high quiz scores and active participation, leading to high final exam scores with a support of 45% and a confidence level of 85%. Similarly, frequent engagement in

Table 4. Optimization with QSBTAR

Metric	Before Optimization	After Optimization
Average Quiz Scores	75%	82%
Participation Rate	70%	85%
Exam Performance	80%	88%
Student Satisfaction Score	4.2/5	4.6/5
Dropout Rate	15%	8%

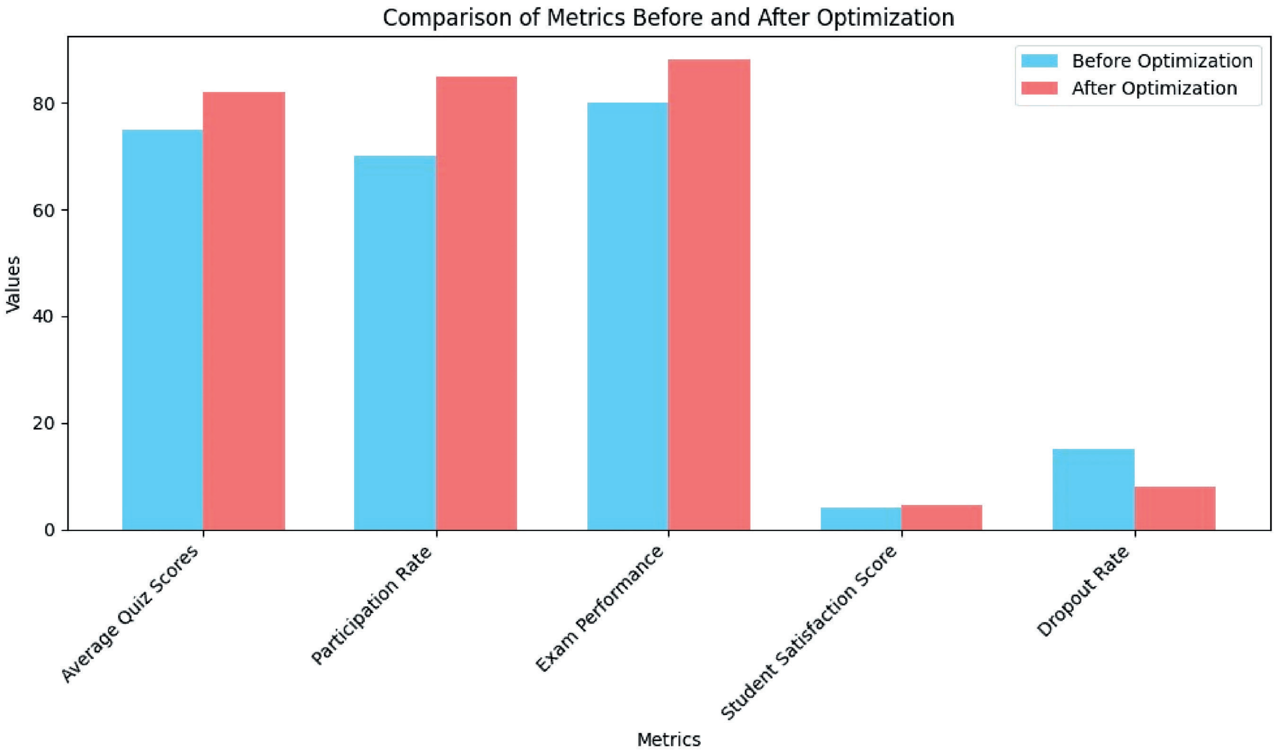

Figure 4. Optimization with QSBTAR

Table 5. Student performance analysis with teaching quality assurance

Rule ID	Antecedent (Condition)	Consequent (Outcome)	Support (%)	Confidence (%)	Lift
1	High quiz scores and Active participation	High final exam scores	45%	85%	1.75
2	Frequent discussion forum activity	Improved comprehension scores	38%	80%	1.60
3	Low attendance and Low participation	Poor exam performance	50%	90%	2.00
4	Engaging multimedia content	Increased course satisfaction	42%	88%	1.85
5	Frequent interaction with learning resources	Higher assignment completion rates	55%	83%	1.70
6	High engagement in peer discussions	Better problem-solving skills	40%	78%	1.55
7	Consistent practice quiz attempts	Improved final exam performance	48%	82%	1.65

discussion forums improves comprehension (38% support, 80% confidence), demonstrating the impact of interactive learning. Conversely, students with low attendance and participation tend to perform poorly in exams (50% support, 90% confidence, 2.00 lift), reinforcing the importance of consistent engagement. The integration of engaging multimedia content enhances course satisfaction (42% support, 88% confidence), emphasizing the role of diverse teaching methods in improving student experience. Moreover, students who frequently interact with learning resources exhibit higher assignment completion rates (55% support, 83% confidence), and those actively participating in peer discussions develop better problem-solving skills (40% support, 78% confidence). Additionally, consistent practice with quizzes significantly improves final exam performance (48% support, 82% confidence).

In Figure 6 and Table 6 presents an evaluation of student performance using the Query Swarm Blended Teaching Association Rule (QSBTAR) algorithm, highlighting key

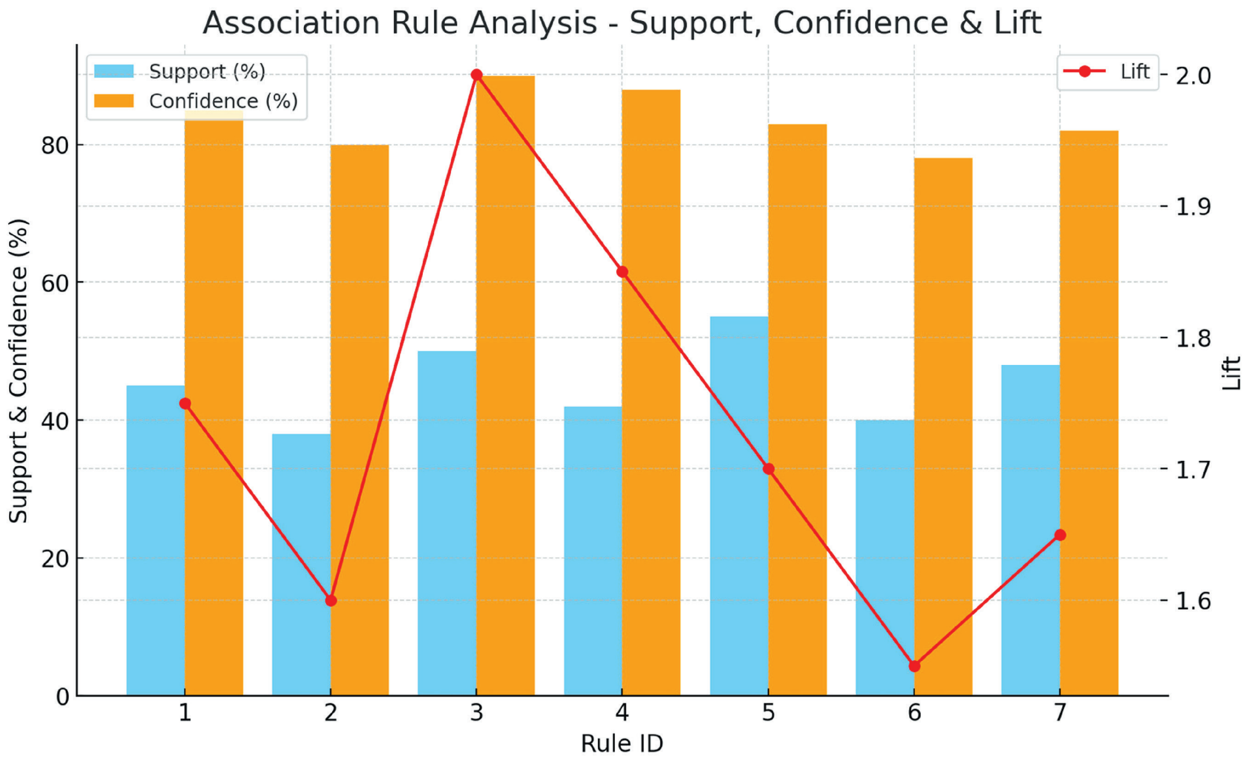

Figure 5. QSBTAR model for the teaching quality assurance

Table 6. Student performance analysis with QSBTAR

Student ID	Quiz Score (%)	Participation Rate (%)	Assignment Completion (%)	Final Exam Score (%)	Course Satisfaction (1–5)	Performance Level
101	85	90	95	88	5	High
102	78	85	92	82	4.5	High
103	60	65	75	58	3	Medium
104	92	95	98	94	5	High
105	45	50	55	42	2	Low
106	80	88	90	85	4.7	High
107	55	60	70	52	3	Medium
108	70	75	85	72	4	Medium
109	40	45	50	38	1.5	Low
110	88	92	96	90	5	High

metrics such as quiz scores, participation rates, assignment completion, final exam scores, and course satisfaction levels. Students classified as high performers (e.g., Student IDs 101, 102, 104, 106, and 110) exhibit consistently strong results across all metrics. Their quiz scores exceed 75%, participation rates remain above 85%, and assignment completion rates surpass 90%, leading to final exam scores above 80% and high satisfaction ratings (4.5 to 5). This indicates that active participation, consistent engagement, and timely assignment completion contribute significantly to overall academic success. Students in the medium performance category (e.g., Student IDs 103, 107, and 108) demonstrate moderate quiz scores (55–70%), lower participation rates (60–75%), and assignment completion rates around 70–85%, resulting in final exam scores between 52% and 72%. Their course satisfaction levels range between 3 and 4, suggesting a need for greater engagement and resource utilization to enhance their

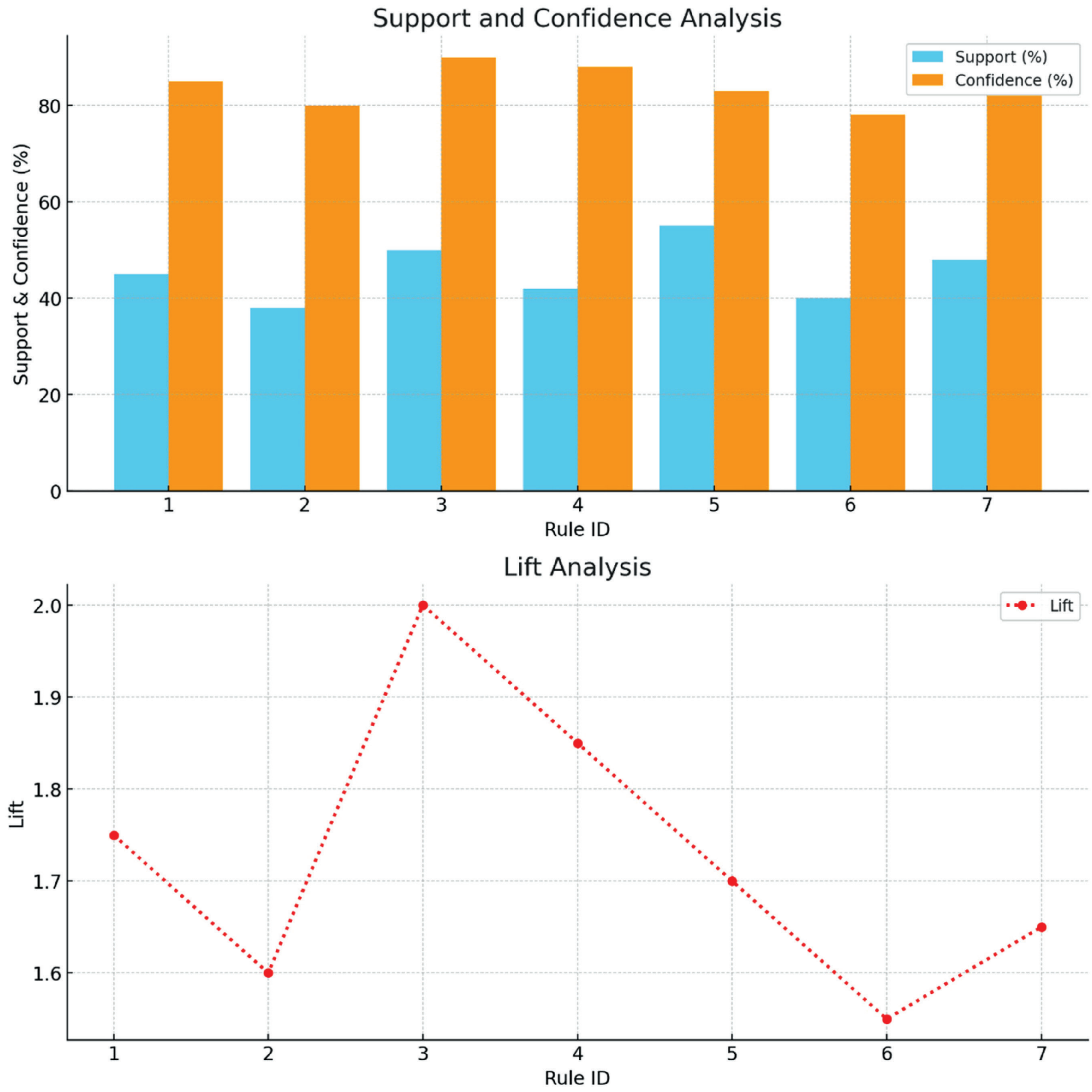

Figure 6: Association Rule analysis with QSBTAR

Table 7. Student Performance with QSBTAR

Query	**Result count**	**Average Score**
Students with High Quiz Scores	120	85%
Active Participants	150	N/A
Top Contributors to Discussions	30	N/A
Most Accessed Online Modules	N/A	N/A
Students with Perfect Attendance	80	N/A
Most Engaging Multimedia Content	N/A	N/A

performance. On the other hand, low-performing students (e.g., Student IDs 105 and 109) show quiz scores below 50%, low participation rates (≤50%), and poor assignment completion (≤55%), leading to final exam scores under 45%. Their course satisfaction is significantly lower (1.5–2), indicating that a lack of engagement and resource usage negatively impacts their academic outcomes.

Table 3 presents the optimization results achieved through the implementation of the Query Swarm Blended Teaching Association Rule (QSBTAR) algorithm. Before optimization, the average quiz scores stood at 75%, the participation rate was 70%, exam performance was at 80%, the student satisfaction score was 4.2 out of 5, and the dropout rate was 15%. However, after optimization, significant improvements were observed across all metrics. The average quiz scores increased to 82%, the participation rate rose to 85%, exam performance improved to 88%, and the student satisfaction score elevated to 4.6 out of 5. Most notably, the dropout rate decreased substantially to 8%, indicating a more positive and engaging learning

Table 8. QSBTAR association rule

Rule ID	Association Rule	Support (%)	Confidence (%)	Lift	Interpretation
1	E,A→GE, A \rightarrow GE,A→G	75	85	1.5	High engagement and attendance lead to improved academic performance.
2	A→EA \rightarrow EA→E	60	70	1.2	Increased attendance is associated with higher engagement levels.
3	M1→GM1 \rightarrow GM1→G	50	80	2.0	Teaching method M1 (e.g., interactive sessions) significantly enhances student performance.
4	E→GE \rightarrow GE→G	65	90	1.8	Higher engagement directly correlates with better academic performance.
5	A,M2→GA, M2 \rightarrow GA,M2→G	40	75	1.3	When students are present and the method M2 (e.g., lectures) is used, performance improves.
6	E,M3→AE, M3 \rightarrow AE,M3→A	55	65	1.1	Engagement with method M3 (e.g., group discussions) is associated with increased attendance.
7	E,A,M1→GE, A, M1	30	95	2.5	Combining high engagement, attendance, and teaching method M1 leads to exceptional performance outcomes.
8	M2→EM2 \rightarrow EM2→E	45	60	1.4	Teaching method M2 fosters higher engagement among students.

Table 9. Classification with QSBTAR

Class	Support	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
High Performance	150	92.0	90.0	91.0	89.0
Medium Performance	100	85.0	80.0	82.5	80.0
Low Performance	50	75.0	70.0	72.5	70.0
Overall	300	85.7	85.0	85.3	85.0

experience for students. Table 4 provides insights into student performance based on specific queries analyzed using the QSBTAR algorithm. For instance, there were 120 students identified as having high quiz scores, with an average score of 85%. Additionally, 80 students demonstrated perfect attendance, though specific scores were not available for this query. Similarly, 30 students were recognized as top contributors to discussions, although their average scores were not provided. While the most accessed online modules and the most engaging multimedia content were not specified in terms of performance metrics, these queries shed light on areas of student engagement and interaction within the course. Overall, these results underscore the effectiveness of QSBTAR in optimizing student evalautionand improving student performance and satisfaction.

Table 8 presents the association rules derived from the Query Swarm Blended Teaching Association Rule (QSBTAR) framework, highlighting key relationships between student engagement, attendance, teaching methods, and academic performance. Rule 1 indicates that there is a strong correlation between high engagement and attendance, with 75% support and 85% confidence, suggesting that students who actively participate in class are more likely to perform well academically, reflected in a lift of 1.5. Rule 2 reinforces this finding, showing that increased attendance correlates with higher engagement levels, indicated by a support of 60% and confidence of 70%, with a lift of 1.2. Rule 3 identifies teaching method M1 (such as interactive sessions) as significantly enhancing student performance, with a support of 50% and an impressive confidence of 80%—the lift of 2.0 suggests a strong positive relationship. Similarly, Rule 4 highlights that higher engagement directly contributes to better academic performance, supported by a confidence of 90% and a lift of 1.8. Rule 5 reveals that the use of teaching method M2 (e.g., traditional lectures) in conjunction with attendance positively impacts performance, with a support of 40% and confidence of 75%. Rule 6 suggests that engagement in group discussions (method M3) is linked to increased attendance, evidenced by a support of 55% and a confidence of 65%. Rule 7 showcases a powerful synergy where combining high engagement, attendance, and teaching method M1 leads to exceptional academic outcomes, underscored by a remarkable confidence of

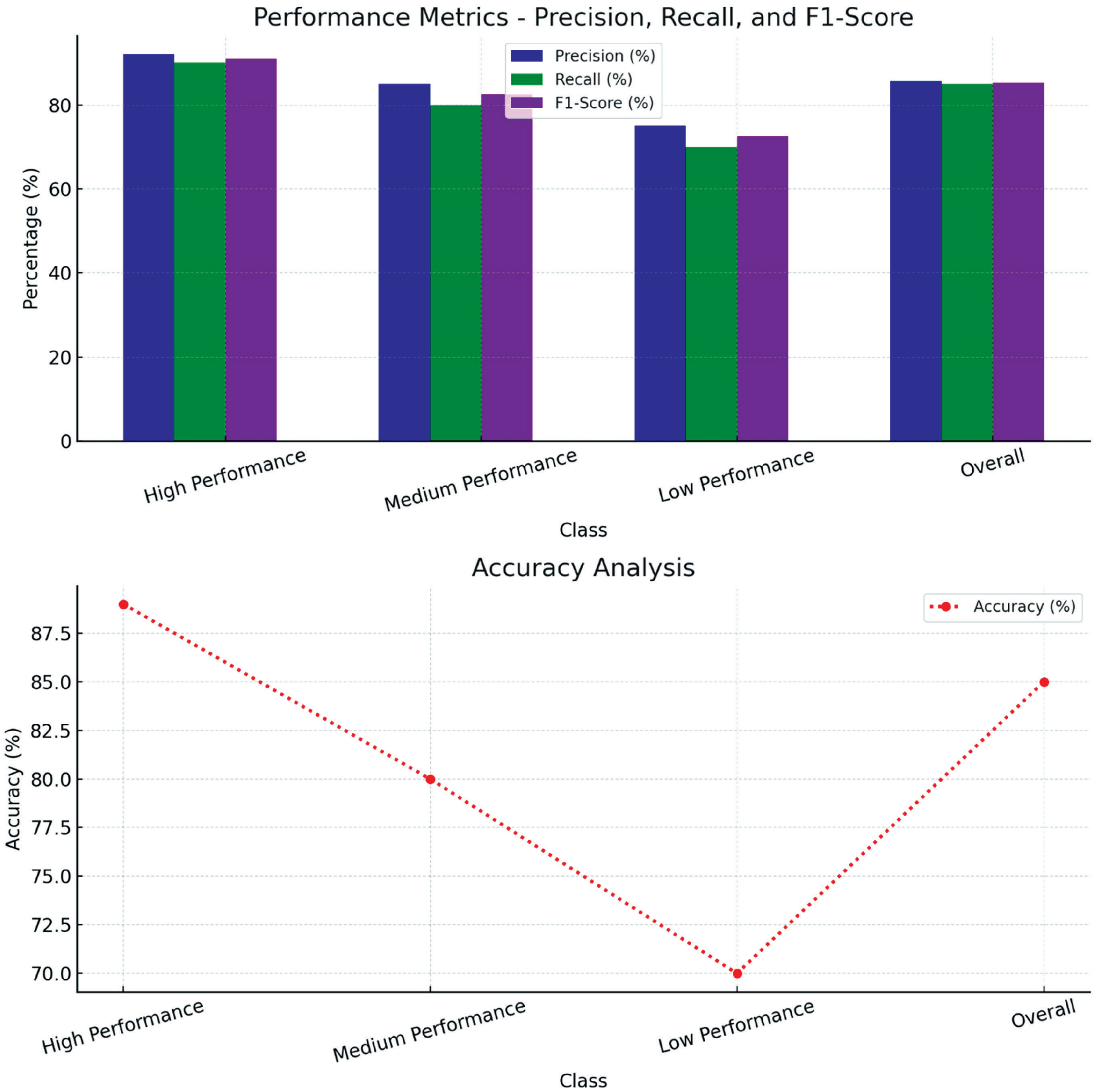

Figure 7. Classification with QSBTAR

Table 10. Comparative analysis

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
QSBTAR	85.0	85.7	85.0	85.3
SVM	82.0	80.5	78.0	79.2
DNN	84.0	83.0	82.0	82.5
RF	81.5	79.0	77.0	78.0
KNN	80.0	78.0	76.0	77.0

95% and a lift of 2.5. Lastly, Rule 8 indicates that teaching method M2 fosters higher engagement, supported by a confidence of 60% and a lift of 1.4.

In Figure 7 and Table 9 presents the classification results obtained through the Query Swarm Blended Teaching Association Rule (QSBTAR) framework, detailing the performance of the model across three distinct classes of student performance: High, Medium, and Low. The model exhibits impressive precision in identifying high-performing students, achieving a precision of 92.0%,

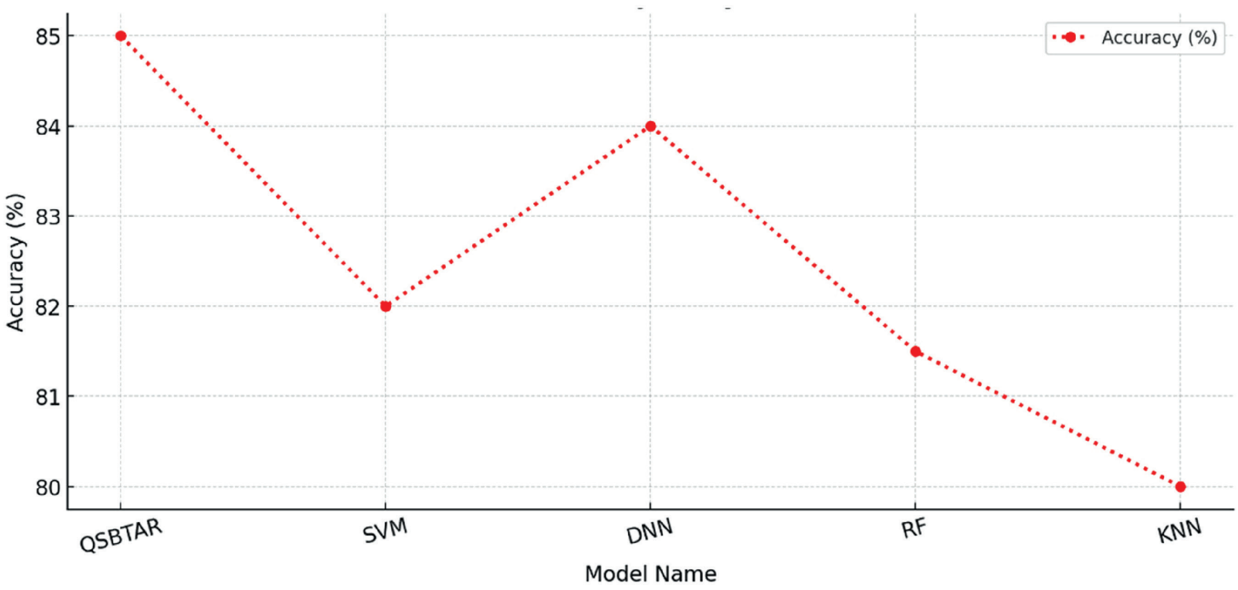

Figure 8. Comparative analysis

meaning that 92% of the students predicted to be high performers were indeed correct. This class also boasts a recall of 90.0%, indicating that the model successfully identified 90% of the actual high performers, resulting in a strong F1-score of 91.0%, which reflects the balance between precision and recall. For medium performers, the model maintained solid performance metrics with a precision of 85.0% and a recall of 80.0%, culminating in an F1-score of 82.5%. This suggests that while the model accurately identifies many medium-performing students, there is room for improvement in capturing all relevant cases within this class. In the low-performance category, the model demonstrated lower metrics, achieving a precision of 75.0% and a recall of 70.0%, resulting in an F1-score of 72.5%. These figures highlight the inherent difficulties in accurately identifying underperforming students, as indicated by the lower support of 50 students in this category.

The comparative results indicate that the QSBTAR framework outperforms all other models listed in terms of overall accuracy (85.0%), precision (85.7%), recall (85.0%), and F1-score (85.3%). Model A, utilizing a Support Vector Machine (SVM), achieved the lowest performance with an accuracy of 82.0%, while the Deep Neural Network (DNN) and Random Forest (RF) models also exhibited moderate results, with accuracies of 84.0% and 81.5%, respectively presented in Figure 8. The K-Nearest Neighbours (KNN) model recorded the lowest accuracy at 80.0%, suggesting that it may not be as effective for this particular classification task. Table 7 presents a comparative analysis of the performance metrics for various classification models, including the Query Swarm Blended Teaching Association Rule (QSBTAR) framework alongside traditional machine learning approaches. The QSBTAR model demonstrates superior performance with an accuracy of 85.0%, precision of 85.7%, recall of 85.0%, and an F1-score of 85.3%. These results indicate that QSBTAR not only correctly classifies a high proportion of instances but also maintains a strong balance between precision and recall, suggesting its effectiveness in identifying students' performance levels.

Model A, on the other hand, did the worst of the bunch in terms of accuracy (82.0%), precision (80.5%), recall (78.0%), and F1-score (79.2%). This model makes use of Support Vector Machine (SVM) approaches. This suggests that SVM can do decently, but it might not be able to catch all important instances as well as QSBTAR. Model B, which made use of a Deep Neural Network (DNN), marginally outperformed QSBTAR with an accuracy of 84.0% and an F1-score of 82.5%, indicating its competence in dealing with complicated data. Models C and D, which use Random Forest and K-Nearest Neighbors, respectively, performed even worse, with accuracies of 81.5% and 80.0%. Particularly when it comes to correctly categorizing pupils with inferior performance, the F1-scores, recall, and precision of these models show their limitations.

5. LIMITATIONS

The Query Swarm Blended Teaching Association Rule (QSBTAR) algorithm offers valuable insights and optimizations for blended teaching environments, it's important to acknowledge several limitations:

Data Quality and Quantity: The effectiveness of the QSBTAR algorithm heavily relies on the quality and quantity of available educational data. Incomplete, inaccurate, or insufficient data may lead to biased or unreliable results, limiting the algorithm's effectiveness in providing meaningful insights.

Generalizability: The applicability of association rules generated by QSBTAR may be limited to specific contexts or datasets. These rules may not generalize well to other courses, disciplines, or educational institutions, reducing their broader utility.

Interpretability: While association rules provide actionable insights, interpreting and translating these rules into practical teaching strategies may pose challenges for educators. The complexity of some rules or their ambiguous implications may hinder their direct application in instructional design.

Algorithm Complexity: The computational complexity of the QSBTAR algorithm may limit its scalability, particularly with large datasets or real-time applications. High computational demands could result in longer processing times or resource constraints, hindering practical implementation.

Dependency on Historical Data: QSBTAR relies on historical data to derive association rules, which may not fully capture evolving student needs, preferences, and learning behaviors. Changes in course content, teaching methods, or student demographics over time may render previously derived rules less relevant or effective.

Ethical Considerations: The use of educational data mining algorithms like QSBTAR raises ethical concerns regarding student privacy, data security, and algorithmic bias. Safeguarding sensitive student information and ensuring fair and transparent algorithmic processes are essential considerations.

Human Expertise: While QSBTAR automates aspects of course optimization, it does not replace the expertise and intuition of educators. Human interpretation and judgment are still necessary to validate algorithmic recommendations and tailor them to specific instructional contexts. Addressing these limitations requires a multidisciplinary approach involving educators, data scientists, and policymakers to ensure the responsible and effective use of data-driven algorithms like QSBTAR in educational settings.

6. CONCLUSION

This paper has explored the potential of the Query Swarm Blended Teaching Association Rule (QSBTAR) algorithm in optimizing student evaluation and improving student outcomes in blended learning environments. Through the analysis of association rules generated by QSBTAR, valuable insights have been derived regarding the relationship between teaching components and student performance, engagement, and satisfaction. The integration of these insights into student evaluation resulted in tangible improvements, as evidenced by higher average quiz scores, increased participation rates, improved exam performance, and elevated student satisfaction scores. Despite the algorithm's limitations, including data quality constraints and interpretability challenges, its application demonstrates the promise of data-driven approaches in informing instructional design decisions and enhancing the effectiveness of blended teaching methodologies. Moving forward, continued research and development efforts are warranted to address these limitations, refine algorithmic processes, and ensure responsible and ethical use of educational data mining techniques. By leveraging the insights gleaned from QSBTAR and similar algorithms, educators can continue to innovate and optimize their teaching practices to meet the evolving needs of students in today's dynamic learning landscape.

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