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A Fuzzy Logic Approach for Student Performance and Exam Integrity Assessment in a Web-Based Smart Quiz System in Higher Education

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ABSTRACT

Purpose – This research aims to develop a Web-Based Smart Quiz System that integrates performance analytics and user behavior monitoring to support more objective and comprehensive learning evaluations. The problem raised is the limitations of the online quiz system in combining fuzzy logic-based performance analysis with exam integrity supervision on the system dashboard.

Design/methods/approach – This system is developed using a prototype model. Student performance and exam integrity were analyzed using a Mamdani fuzzy logic approach based on four input variables, namely score percent, integrity, attempt count, and time ratio. For fuzzy inference processing, warning count, tab switch count and fullscreen exit count were aggregated into a single integrity violations index, which was used as the integrity variable. The system is also equipped with examination integrity features, an analytics dashboard, and question item analytics to support adaptive evaluation and examination integrity assessment.

Findings – The results showed that 81 quiz attempts were classified into 33 Superior, 39 Good, 7 Enough, and 2 Needs Coaching. Risk analysis showed that 79 attempts were in the Safe category, while 2 attempts required further attention. These results indicate that the proposed system can support adaptive performance evaluation while facilitating examination integrity monitoring during online assessment.

Research implications/limitations – The study was conducted within a single higher education institution and relied on predefined membership functions and rule bases. Future studies should involve larger and more diverse populations and explore longitudinal validation of the model.

Originality/value – This study presents a prototype-based integrated assessment platform that combines fuzzy performance evaluation, examination integrity monitoring, user behaviour analytics, and question item analytics within a single web-based Smart Quiz System. The proposed platform is intended as a decision-support tool for learning evaluation and provides a foundation for future validation and enhancement using larger datasets and advanced analytics methods.

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INTRODUCTION

The development of digital technology in the field of education has driven significant changes to the learning evaluation process, especially through the implementation of web-based quiz and exam systems. Digital evaluation systems are widely used because they are able to improve the efficiency of question distribution, automate assessments, flexibility of access, and support distance learning in a modern educational environment. The development of learning management systems and learning analytics technology further strengthens the implementation of digital learning by providing various features for real-time monitoring of learning activities Thuy et al. (2025). Most quiz systems that are created today still focus on the final result in the form of scores obtained by participants without considering the behavior of the user during the exam process (Özseven & Çağman, 2022). This approach may not fully and objectively represent the actual quality of student performance. The integrity of online exams is also still a major challenge because the monitoring mechanisms available are generally limited to detect potential violations during the exam. The increase in the use of digital learning in higher education requires an evaluation system that is not only able to measure academic achievement, but also can analyze user activities, the level of risk of violations, the consistency of problem work, and the overall performance of participants. A learning evaluation system is needed that is able to integrate academic performance analysis and exam integrity monitoring adaptively in one integrated platform.

Research on learning analytics has been done to support the learning assessment and evaluation process. Thuy et al. (2025) developed a web-based learning analytics dashboard capable of visualizing student quiz performance in real-time and increasing student engagement in the learning process. The research is still limited to the aspect of performance visualization and has not utilized artificial intelligence or user behavior monitoring during the exam. Jayashanka et al. (2022) reported that learning analytics dashboards can increase student motivation and engagement in learning. However, the system developed is still descriptive and does not support adaptive analysis or automated decision-making based on artificial intelligence. Herodotou et al. (2025) showed that learning analytics can visualize student learning progress while providing data-driven recommendations. The progress of learning analytics visualization is a bright spot for knowing the factors of student learning success. Shannan et al. (2023) explained that learning analytics enables institutions to track student performance, identify factors affecting learning success, and provide personalized feedback. Learning analytics is the process of collecting, measuring, analyzing, and reporting learning data that aims to understand and optimize the student learning process (Stanja et al., 2023). Analytical learning models can be used to describe the continuous development of student learning to facilitate the process of monitoring and evaluating learning (Wu et al., 2024). Complex learning data is used to build computational models that are able to represent the learning process as a whole, Ouyang, Xu, et al. (2023).

Representation of learning data from a model that is built contains a record of learning activities. Bernacki et al. (2025) demonstrated that digital activities recorded on learning platforms can be used to validate self-regulated learning processes and provide a more objective picture of student learning progress. Activities in learning analytics utilize data sources, analytical methods, and predictive modeling to produce interventions aimed at improving students' learning experience (Liu et al., 2025). One of the main goals of learning analytics is to provide a personalized learning experience through feedback, recommendations, and learning resources that meet the needs of students (Cabi & Turkoglu, 2025). Alam et al. (2023) found that real-time visual information helps students understand their learning progress and encourages more active participation in learning activities. Lahza et al. (2023) showed that interaction data recorded in learning systems can reveal learning behavior patterns and their relationship with academic performance. The learning analytics dashboard functions as a means of reflection on student learning behavior so that it can help students set learning goals and implement the necessary corrective actions (Vreugd et al., 2025).

The fuzzy logic approach has been widely applied in evaluation and decision support because of its ability to handle uncertainty and produce more flexible decisions than the usual scoring method. The student performance evaluation model is based on fuzzy logic in distance learning by considering various academic parameters. Özseven and Çağman (2022) proposed a fuzzy logic-model student performance evaluation model capable of producing more objective assessments than traditional evaluation. The research has not integrated learning analytics or monitoring the integrity of exams based on user behavior. Abdymanapov et al. (2021) applied a fuzzy expert system to conduct security risk assessments in learning management systems. The system is able to produce an accurate risk assessment, but it still focuses on security and has not considered student performance in the context of learning. This is due to the shift to digital learning and assessment, increasing the chances of students using external platforms to obtain unauthorized assistance during the evaluation process (Lancaster & Cotarlan, 2021). The integration of artificial intelligence and learning analytics has great potential in supporting data-driven pedagogical decision-making (Sajja et al., 2025). The implementation is still focused on learning analytics and has not yet led to a Smart Quiz System that is integrated with exam integrity features and live performance evaluation. Papakostas et al. (2023) demonstrated that fuzzy logic can be used to build adaptive learning systems capable of adjusting difficulty levels according to student performance. Shobana and Kumar (2022) showed that intelligent quiz system can leverage user interaction data during assessments to generate more comprehensive evaluations. AI-driven learning analytics has the potential to provide feedback on student performance both individually and in groups, so as to support the improvement of learning quality, Ouyang, Wu, et al.(2023).

Based on the literature review, there are several research gaps that have not been widely developed. First, most learning analytics research still focuses on data visualization and performance monitoring in a descriptive manner without the integration of artificial intelligence-based intelligent evaluation. Second, research related to fuzzy logic in the field of education is generally only used for academic performance evaluation without considering aspects of exam integrity and user behavior during the question processing process. Third, there have not been many studies that integrate performance evaluation, exam integrity monitoring, and real-time analytics dashboards into a single web-based Smart Quiz System. Most online evaluation systems still use a conventional assessment approach based on final scores so that they are not able to produce a more adaptive and comprehensive performance analysis. A comparison of relevant studies and research gaps is presented in Table 1.

Table 1. Comparison of Related Studies and Research Gaps

Study	Main contribution	Method	Analytics Focus	Limitation
Thuy et al. (2025)	Real-time quiz performance visualization and learner feedback	Learning analytics visualization	quiz performance monitoring and feedback	does not provide intelligent performance evaluation or examination integrity assessment
Jayashanka et al (2022)	technology enhanced learning analytics dashboard (TELA)	Learning analytics dashboard	student engagement, learning progress, and quiz analytics	focus descriptive analytics without intelligent decision-making models
Ozseven & Cagman (2022)	student performance evaluation in distance learning	Mamdani fuzzy logic	academic performance assessment	does not incorporate behavioural indicators or examination integrity monitoring
Abdymanapov et al. (2021)	LMS security risk assessment	Mamdani fuzzy logic	information security risk evaluation	focuses on system security rather than student

				learning performance
Shobana & Kumar (2022)	intelligent assessment using non-verbal behaviour detection	Random forest	learner behaviour and knowledge acquisition analysis	requires computer vision and does not provide learning analytics dashboard or integrity scoring
proposed Smart Quiz System	integrated learning evaluation and exam integrity analytics	Mamdani fuzzy logic and learning analytics	academic performance, user behaviour, exam integrity, and item analytics	integrate multiple analytical dimensions within a single platform

To address this gap, this study proposed a web-based Smart Quiz System that integrates learning analytics, fuzzy logic, and exam integrity monitoring. The fuzzy inference model utilizes four input variables, namely score percent, integrity, attempt count, and time ratio, to generate fuzzy performance scores, student performance category, and exam violation risk level. For fuzzy inference processing, warning count, tab switch count, and fullscreen exit count are aggregated into a single integrity variable representing examination integrity behaviour. The prototype method is used in system development because it allows the development process to be carried out iteratively through the stages of needs identification, design, implementation, testing, and evaluation. Fuzzy Logic is used to classify student performance based on a combination of academic parameters and user activity during exams.

The proposed system represents a prototype-based integrated assessment platform that combines fuzzy performance evaluation, examination integrity monitoring, user behaviour tracking, and learning analytics within a single web-based environment. Rather than relying solely on conventional score-based assessment, the platform is designed to provide a more comprehensive decision-support mechanism by incorporating both academic performance indicators and examination behaviour data. The system also provides an analytics dashboard that assists lecturers in monitoring student performance, examination integrity indicators, and potential violations through an integrated visualization environment. Therefore, this study aims to develop and implement a prototype-based integrated assessment platform that combines fuzzy performance evaluation, learning analytics, and examination integrity monitoring within a web-based Smart Quiz System for higher education.

METHOD

This research uses the prototype method to develop a web-based Smart Quiz System. This prototype model allows system development to be carried out iteratively through the process of identifying needs, designing, implementing, testing, and evaluating until a system that meets the needs of users is obtained (Wiratama et al., 2023). The flow diagram of the prototype model in this study is shown in Figure 1.

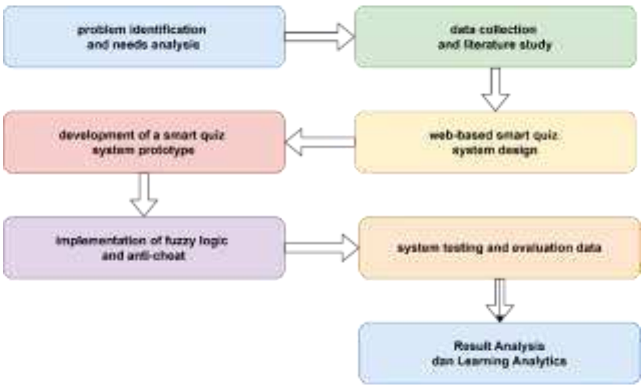

Figure 1. Prototype Method Research Stage

The participants in this research consisted of 58 students from two classes with the same material Artificial Intelligence for Education. The sampling technique used is total sampling because all students who take part in learning evaluation activities using the Smart Quiz System are involved as research subjects. Every student activity during the quiz process is automatically recorded by the system directly in the classroom and used as performance analysis data and exam integrity assessment. This study was conducted as part of regular classroom learning and assessment activities within a higher education course. Formal institutional ethical approval was not obtained because this study was conducted as part of routine classroom teaching and learning activities in Artificial Intelligence course within the Computer Educational Study Program, Faculty of Teacher Training Education, Universitas Mulawarman. The study did not involve medical intervention, vulnerable populations, or the collection of personally identifiable or sensitive information. Prior to the implementation of the quizzes, all students were informed that their quiz interaction data, including quiz attempts and system-generated behavioural logs, would be collected anonymously and used solely for research purposes. Participation was voluntary, informed consent was obtained from all participants, and all analyses were performed using anonymized data to protect participants' privacy.

The system was evaluated using data collected from 58 undergraduate students enrolled in two classes within Computer Education Study Program, Faculty of Teacher Training and Education, Universitas Mulawarman. Class A consisted of 31 students who completed one online quiz on Artificial Intelligence in Education, resulting in 31 recorded quiz attempts. Class B consisted of 27 students who participated in two quiz sessions covering Artificial Intelligence in Education and Fuzzy logic. Among these students, 23 completed both quizzes, while two students completed only the Artificial Intelligence in Education quiz and another two students completed only the Fuzzy Logic quiz. Consequently, Class B contributed 50 recorded quiz attempts. Overall, the dataset comprised 58 participating students and 81 recorded quiz attempts. Each quiz submission was treated as an independent evaluation record and analyzed separately using the proposed fuzzy model. Therefore, all performance and examination integrity analyses reported in this study were conducted at the attempt level rather than the student level. The distribution of participants and quiz attempts used in this study is summarized in Table 2.

Table 2. Distribution of Participants and Quiz Attempts

Class	Students	Quiz Activity	Quiz Attempts
Class A	31	Artificial Intelligence in Education	31
Class B	23	Artificial Intelligence in Education and Fuzzy Logic	46
Class B	2	Artificial Intelligence in Education only	2
Class B	2	Fuzzy Logic only	2
Total	58	-	81

The research instrument consists of two main components, namely the system instrument and the fuzzy analytics instrument. The system was developed using a web-based client-server architecture consisting of the user layer, frontend, backend API, AI analytics layer, security and monitoring, data storage, and dashboard and output layer. The system provides quiz management features, question processing, user activity monitoring, analytics dashboard, and evaluation report reporting. The second part of the quiz evaluation instrument uses a fuzzy Mamdani inference system integrated into the Smart Quiz System to analyze student performance and the level of risk of exam violations adaptively. The fuzzy model is designed by taking into account academic indicators and user behavior during the quiz process so that the evaluation is not only based on the final score, but also pays attention to the integrity of the exam implementation. The fuzzy inference process used in this study is shown in Figure 2.

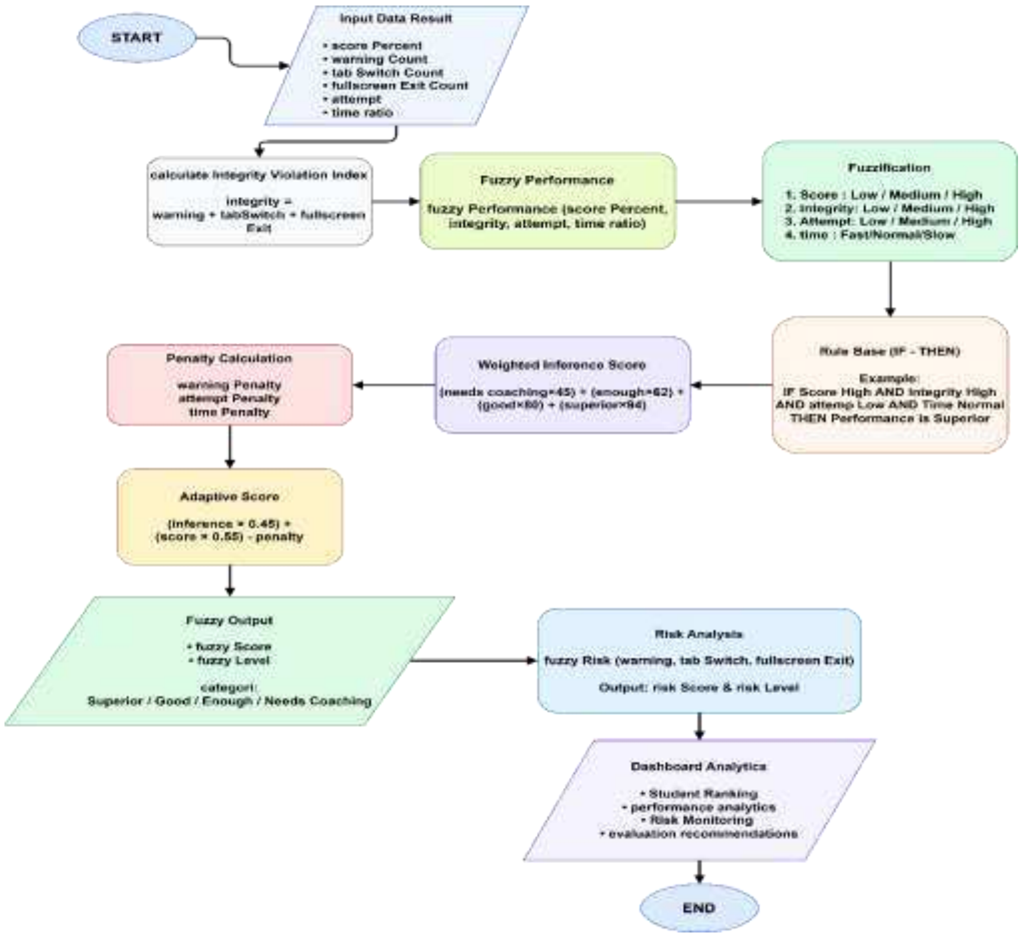

Figure 2. Fuzzy Logic flowchart on Smart Quiz System

The fuzzification stage is carried out by converting the crisp values to a fuzzy membership degree based on the predetermined membership function. The next stage is the rule base fuzzy which is an inference process using if-then rules based on fuzzy Mamdani. Next, the rule aggregation process and the calculation of the weighted inference score are carried out. The defuzzification process to produce the final score of student performance uses the weighted adaptive score approach. Penalties are obtained based on the number of warnings and user activity during the work. In addition to generating a fuzzy performance score, the system also conducts risk analysis based on user activity during the quiz. The risk score is calculated using the warning count parameters, tab switch count, and fullscreen exit count.

The membership functions for the input and output variables are shown in Table 3. The score percent, integrity, attempt count variables are classified into Low, Medium, and High categories. Time ratio variables are classified into the categories of Slow, Normal, and Fast. Output fuzzy consists of performance score and risk score. The membership function output performance values are classified into Needs Coaching, Enough, Good, and Superior, while the risk level is classified into Safe, Review, and High Risk.

Table 3. Input Membership Function

Variable	Type	Linguistic Category	Parameters
Score Percent	Input	Low	(0, 0, 45, 60)
		Medium	(45, 65, 85)
		High	(75, 90, 100, 100)

Integrity (Violation Index)	Input	Low	(5, 8, 15, 15)
		Medium	(2, 5, 8)
		High	(0, 0, 1, 3)
Attempt Count	Input	Low	(1, 1, 1.2, 2)
		Medium	(1.5, 2.5, 3.5)
		High	(3, 4,5, 5)
Time Ratio	Input	Slow	(0.90, 1.15, 1.50, 1.50)
		Normal	(0.30, 0.70, 1.10)
		Fast	(0, 0, 0.20, 0.45)
Performance Score	Output	Needs Coaching	(0, 0, 45, 55)
		Enough	(50, 62, 72)
		Good	(68, 80, 88)
		Superior	(85, 92, 100, 100)
Risk Score	Output	Safe	(0, 0, 20, 35)
		Review	(25, 50, 70)
		High Risk	(60, 80, 100, 100)

The membership function boundaries were established based on educational assessment principles, commonly applied grading standards in higher education, and observed online examination behaviour during the prototype development process. The score percent variable was categorized according to academic achievement levels, where lower values indicate insufficient mastery and higher values represent strong learning outcomes. The attempt count variable was designed to reflect quiz completion behaviour, while the integrity variable was derived from system-monitoring activities, including warning count, tab-switching events, and fullscreen-exit violations. The time ratio variable was defined based on the proportion between actual completion time and the allocated quiz duration. The membership ranges were iteratively refined through system testing and evaluation to ensure that the fuzzy classifications adequately represented student performance and examination behaviour within the smart quiz environment. The selected boundaries were reviewed internally by the research team based on educational evaluation experience, online assessment practices, and the results of iterative prototype testing before being implemented in the final fuzzy inference model.

For the score percent variable, the membership boundaries were aligned with commonly applied higher education grading practices. Scored below 60 were categorized as Low because they generally indicate insufficient mastery of learning outcomes, whereas scores above 75 represent satisfactory to excellent academic achievement. The integrity violation index thresholds were determined according to the observed frequency of warning events, tab-switching activities, and fullscreen-exit violations recorded during prototype testing, where higher values reflected more frequent integrity-related violations. The attempt count boundaries were selected to distinguish between single-attempt completion behaviour and repeated quiz access patterns. The time ratio thresholds were defined based on the proportion between actual completion time and the allocated quiz duration, allowing the system to differentiate fast, normal, and slow completion patterns. The final membership ranges were refined through iterative prototype testing and comparison with the distribution of observed quiz-attempt data to ensure that the resulting classifications reflected realistic assessment behaviours within the smart quiz environment.

The integrity variable represents an integrity violation index derived from the aggregation of warning count, tab-switch count and fullscreen-exit violations recorded during quiz activities. Therefore, lower values indicate higher examination integrity, while higher values indicate a greater number of integrity violations. Consequently, the high category corresponds to low violation frequencies, whereas the low category represents frequent integrity violations during the assessment process. Accordingly, although the numerical input represents an integrity violation index, the membership labels in Table 3 are interpreted as integrity levels rather than violation levels. The integrity variable was constructed by aggregating warning count, tab switch count, and fullscreen exit count. Therefore, these indicators are not modeled as separate fuzzy input variables in Table 2. Accordingly, the fuzzy inference model operates using four fuzzy input variables, namely score percent, integrity, attempt count, and time ratio. The membership functions and fuzzy rules were reviewed internally by the research team throughout the iterative development process. However, formal validation by external experts in educational assessment and fuzzy systems was not conducted and remains an important direction for future research. Accordingly, the current membership functions and fuzzy rule base should be interpreted as a prototype design intended to support decision-making within the Smart Quiz System. The resulting performance and examination integrity classifications are preliminary and should not be interpreted as fully validated assessment outcomes. Future studies involving external experts in educational assessment, learning analytics, and fuzzy systems, as well as empirical calibration using larger datasets, are required to strengthen the validity and generalizability of the proposed model.

The rule base in the Smart Quiz System was developed using the Mamdani fuzzy inference system approach based on a combination of four input variables, namely score percent, integrity score, attempt count, and time ratio. The higher the quiz score and examination integrity, the higher the resulting performance classification. Conversely, activities that show potential violations, such as low integrity, will lower the performance categories that the system provides. A total of 35 fuzzy rules were used to produce a classification of student performance into four categories, namely Needs Coaching, Enough, Good, and Superior. The rules are prepared based on the principles of learning evaluation and exam integrity indicators so that they are able to produce assessments that are more adaptive than the final score-based approach alone. Although four input variables theoretically generate 81 possible rule combinations, only 35 representative rules were implemented in the prototype.

The selected rules were designed to capture the most relevant and educationally meaningful assessment scenarios observed during system development and prototype testing. Several theoretical input combinations produce highly similar educational interpretations and therefore lead to identical or closely related output categories. Consequently, the rule base was constructed using representative combinations rather than explicitly enumerating all 81 theoretical possibilities. Because Mamdani fuzzy inference employs overlapping membership functions, a single input may simultaneously activate multiple rules with different membership degrees. The final classification is therefore determined through rule aggregation and defuzzification based on the activated rules, allowing intermediate input conditions to be evaluated without requiring explicit representation of every possible combination. No observed quiz-attempt records remained unclassified during system testing. The fuzzy rule based on the Smart Quiz System is shown in Table 4.

Table 4. Fuzzy Rule Base of Smart Quiz System

Rule	Score	Integrity	Attempt	Time Ratio	Performance
R1	Low	High	Low	Fast	Needs Coaching
R2	Low	High	Low	Normal	Needs Coaching
R3	Low	Medium	Low	Slow	Needs Coaching
R4	Low	Medium	Low	Fast	Needs Coaching
R5	Low	Medium	Low	Normal	Needs Coaching
R6	Low	Low	Low	Slow	Needs Coaching
R7	Low	Low	Low	Fast	Needs Coaching
R8	Low	Low	Low	Normal	Needs Coaching
R9	Low	High	Low	Slow	Needs Coaching
R10	Medium	High	Low	Fast	Good
R11	Medium	High	Low	Normal	Good
R12	Medium	High	Low	Slow	Enough
R13	Medium	Medium	Low	Fast	Enough

Rule	Score	Integrity	Attempt	Time Ratio	Performance
R14	Medium	Medium	Low	Normal	Enough
R15	Medium	Medium	Low	Slow	Enough
R16	Medium	Low	Low	Fast	Needs Coaching
R17	Medium	Low	Low	Normal	Enough
R18	Medium	Low	Low	Slow	Needs Coaching
R19	High	High	Low	Fast	Good
R20	High	High	Low	Normal	Superior
R21	High	High	Low	Slow	Good
R22	High	Medium	Low	Fast	Good
R23	High	Medium	Low	Normal	Good
R24	High	Medium	Low	Slow	Good
R25	High	Low	Low	Fast	Enough
R26	High	Low	Low	Normal	Good
R27	High	Low	Low	Slow	Enough
R28	Medium	High	Medium	Normal	Enough
R29	High	High	Medium	Normal	Superior
R30	High	Medium	Medium	Normal	Good
R31	High	Low	Medium	Normal	Enough
R32	Low	High	High	Normal	Needs Coaching
R33	Medium	High	High	Normal	Enough
R34	High	High	High	Normal	Good
R35	High	Low	High	Normal	Enough

The examination risk score was calculated using a separate fuzzy risk-analysis procedure based on the Integrity Violation Index. The integrity violation index was obtained by aggregating three behavioural monitoring indicators recorded during quiz activities, namely warning count, tab switch count, and fullscreen exit count, as shown in equation:

$$\text{Integrity Violation Index} = \text{Warning Count} + \text{Tab Switch Count} + \text{Fullscreen Exit}$$

The resulting integrity violation index was then fuzzified into three linguistic categories representing examination integrity conditions: High, Medium, and Low integrity. In this study, lower violation-index values indicate higher examination integrity, whereas higher values indicate more frequent integrity-related violations. The risk analysis employed a separate fuzzy inference mechanism consisting of the rule: (1) IF integrity is High THEN Risk is Safe, (2) IF integrity is Medium THEN Risk is Needs Review, and (3) IF integrity is Low THEN Risk is High Risk. The corresponding output values assigned to these risk categories were 18, 55, and 85, respectively. The final risk score was calculated using weighted average defuzzification based on the activated rule strengths. The resulting risk score was subsequently classified into three risk levels. Risk scores below 35 were categorized as Safe, scores between 35 and 69 were categorized as Needs Review, and scores of 70 or above were categorized as High Risk. The generated risk level was used to support examination integrity monitoring and lecturer decision-making through the analytics dashboard. Fuzzy risk classification rules are shown in Table 5 and score classification thresholds are shown in Table 6.

Table 5. Fuzzy Risk Classification Rules

Integrity Category	Risk Category	Output Value
High	Safe	18
Medium	Needs Review	55
Low	High Risk	85

Table 6. Risk Score Classification Thresholds

Risk score range	Classification
0-35	Safe

35-69	Needs Review
≥ 70	High Risk

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RESULTS AND DISCUSSION

The proposed web-based Smart Quiz System has been successfully developed and implemented to support learning evaluation based on learning analytics and fuzzy logic. The system integrates quiz management features, student activity monitoring, learning analytics, question item analysis, and adaptive performance evaluation in one platform. The implementation of the system allows lecturers to obtain real-time student performance information based on quiz scores and user activities during the evaluation process. The system can also classify student performance using fuzzy logic inference, monitoring quiz activities, one of which is a warning of detected violations. The results of the integration are shown in Figure 3. Instructor dashboard illustration integrates learning analytics, fuzzy performance evaluation, and exam integrity monitoring in a single interface. Several key indicators are presented, including the number of students, quiz participation records, average scores, question items analyzed, fuzzy performance summaries, and risk analysis results. The AI security insight module provides information on potential exam violations, while graphical visualizations support monitoring of score distribution, weekly performance trends, and correctness of answer statistics. This integrated dashboard allows lecturers to get a comprehensive picture of student learning outcomes and exam integrity in real-time. The dashboard summarizes data from 58 participating students and 81 recorded quiz attempts, which serve as the basis for the performance and examination integrity analyses presented in this study. This system is capable of capturing and analyzing student activities during the evaluation process. Bernacki et al. (2025) demonstrated that digital traces can be used to understand student learning behavior and development more comprehensively.

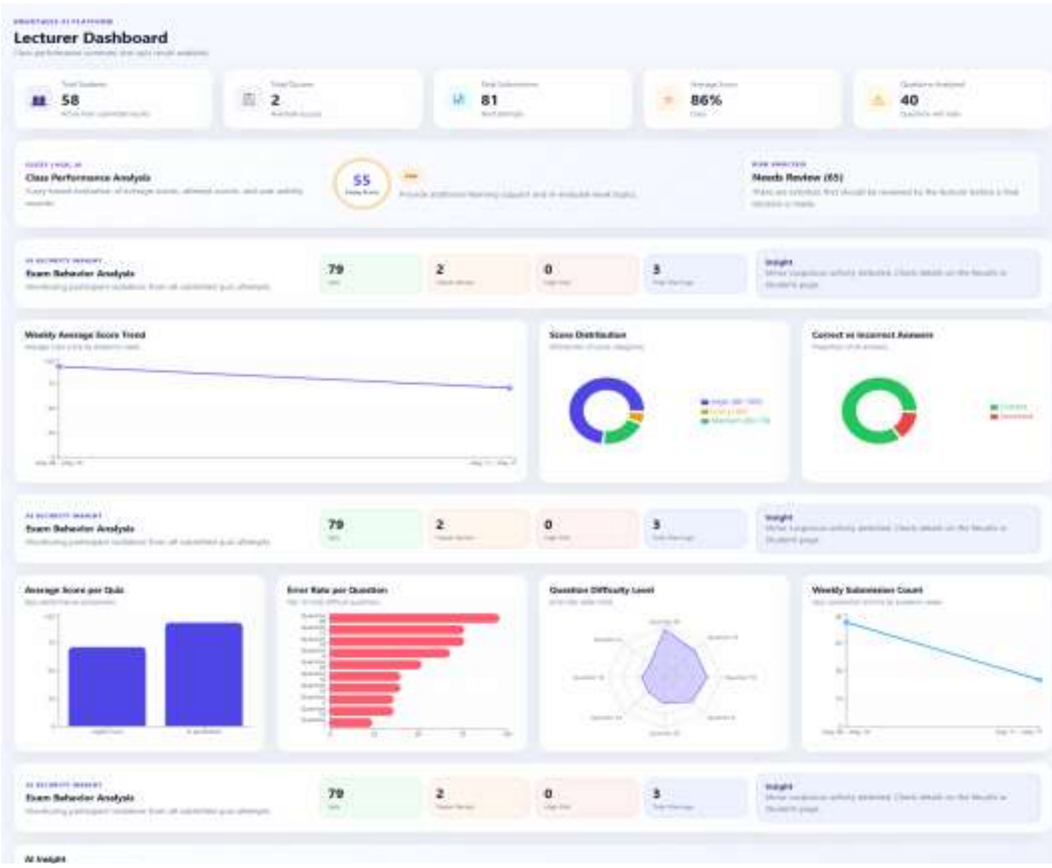

Figure 3. Smart Quiz Analytics Dashboard Integrating Fuzzy Performance Evaluation, Examination Integrity Monitoring, and Learning Analytics

A total of 58 students actively participated in the Smart Quiz System, generating 81 recorded quiz attempts. Since each quiz submission was treated as an independent evaluation record, all performance and examination integrity analyses presented in this section are reported rather than the student level. The average quiz score was 86, with the highest score of 100 and the lowest score of 50. Meanwhile, the average fuzzy performance score produced by the proposed system was 81, indicating that overall student performance was classified in the Good category. The fuzzy performance distribution showed that 33 quiz attempts were classified as Superior, 39 as Good, 7 as Enough, and 2 as Needs Coaching. An example comparison between score-based and fuzzy-based evaluation is shown in Table 7.

Table 7. Illustrative Comparison Between Conventional Score-Based Evaluation and The Proposed Fuzzy-Based Evaluation

Student ID	Quiz Score (%)	Integrity Violation Index	Attempt Count	Time Ratio	Fuzzy Score	Performance Classification
Student 1	95	0	1	0.53	85	Good
Student 2	95	4	1	0.50	74	Needs Coaching
Student 3	95	0	1	0.54	91	Superior
Student 4	95	0	1	0.30	66	Enough

Table 7 demonstrates the adaptive capability of the proposed evaluation model. Although all four students obtained the same quiz score 95%, the final classification differed because the proposed system does not rely solely on score percentage. As illustrated in Figure 2, the quiz score, Integrity Violation Index, Attempt Count, and Time Ratio are processed simultaneously through the fuzzy performance evaluation mechanism. The internal computation incorporates weighted fuzzy inference and adaptive penalty calculation to generate the final Fuzzy Score, which is then used to determine the corresponding Performance classification. Consequently, students with identical quiz scores may receive different performance classifications when their examination integrity conditions or time-efficiency patterns differ. For example, students 1 and 3 obtained the same quiz score and Integrity Violation Index; however, differences in their Time Ratio values resulted in different Fuzzy Scores and performance classifications. Likewise, Student 2 obtained the same quiz score as the others but received a lower Fuzzy Score and was classified as Needs Coaching because of a higher Integrity Violation Index. These results demonstrated that the proposed model evaluates student performance using multiple assessment dimensions rather than relying exclusively on conventional score-based assessment. The performance distribution showed that 33 quiz attempts were classified as Superior, 39 as Good, 7 as Enough, and 2 as Needs Coaching.
These findings indicate that most students achieved Good or Superior performance. In terms of time efficiency, 67 quiz attempts were classified as Fast, while the remaining 14 attempts were classified as Normal. No attempts were classified as Slow. These results indicate that most students were able to complete the quiz efficiently within the allocated time. The examination integrity analysis showed that 79 quiz attempts were classified as Safe, while only 2 attempts required further attention. Based on the risk score thresholds presented in Table 6, attempts classified as Safe exhibited minimal or no recorded examination violations, whereas attempts requiring further attention accumulated higher Integrity Violation Index values due to warning count, tab-switching events, and fullscreen exit violations. These findings indicate a high level of compliance with the examination rules among participants. It should be noted that Examination Integrity Risk Level (Safe, Needs Review, and High Risk) is evaluated independently from the Fuzzy performance Level (Superior, Good, Enough, and Needs Coaching). Consequently, a student may achieve a High performance classification while still receiving a Needs Review status if elevated examination violations are detected, whereas a student classified as Needs Coaching may still receive a Safe status when no significant integrity violations are observed.

The system can also provide a question item analysis feature that is used to identify the difficulty level of each item based on the correct rate and error rate. The results of the analysis are shown in Figure 4. Based on the results of the analysis, some questions show a high level of difficulty because they have a higher error rate compared to the correct rate. This dashboard provides question-level learning analytics through error rate analysis, problem difficulty classification, and response distribution statistics. In addition to identifying difficult questions, this dashboard summarizes the overall quality of the assessment question items by displaying the average error rate, the most difficult and easiest questions, and the proportion of true, false, and unanswered responses. These analytics support lecturers in evaluating the quality of assessments and identifying concepts that need further instructional reinforcement. Question number 26 has a correct rate of 4% and an error rate of 96%, while questions numbers 15 and 19 have a correct rate of 24% and an error rate of 76%, respectively. In addition, question number 9 shows a correct rate of 32% and an error rate of 68%. These results indicate that these items require further evaluation because they have the potential to contain complex concepts, unclear wording, or too high a level of difficulty for students. Most of the questions show a high correct rate and a low error rate. This means that most students are able to understand the material being tested. In addition, there are several questions with a moderate level of difficulty that are able to distinguish students who understand the material and those who do not understand the material optimally.

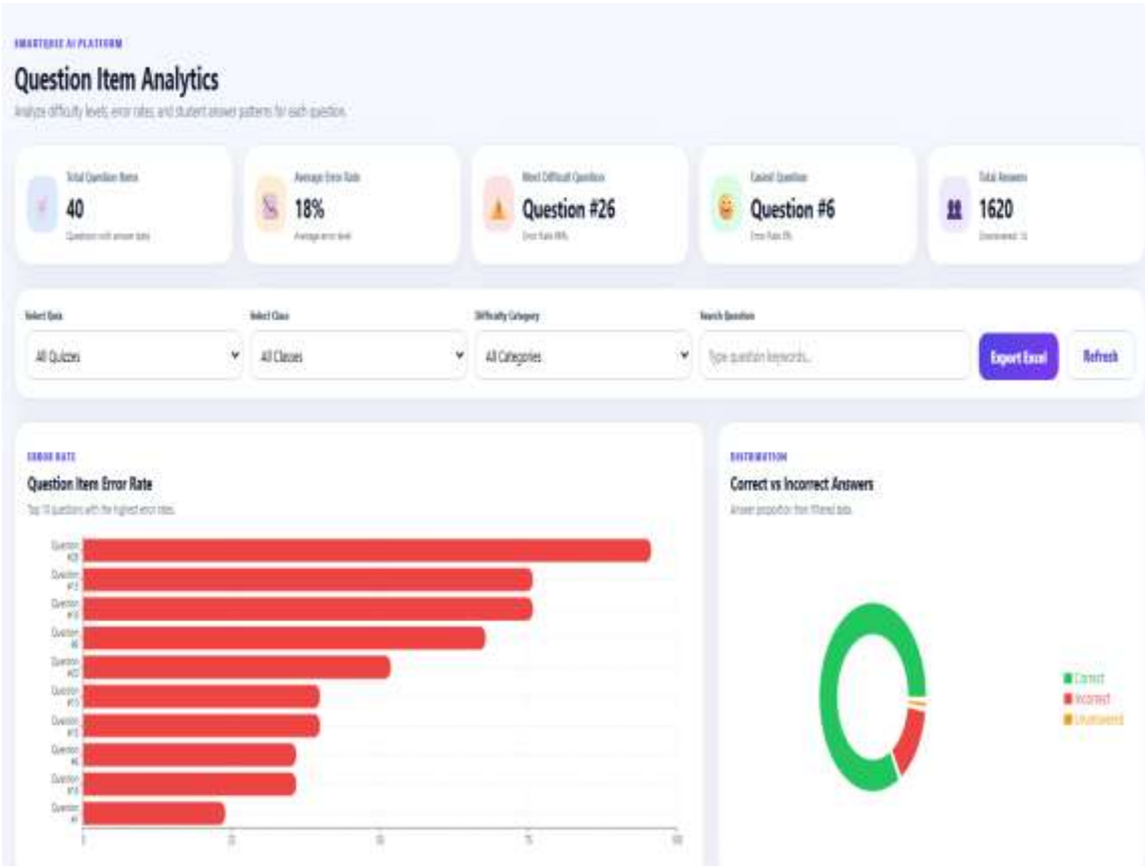

Figure 4. Question Item Analytics Dashboard Showing Error Rate Distribution, Difficulty Analysis, and Response Statistics

A summary of the analytical results is shown in Figure 5. It integrates fuzzy performance evaluation, exam integrity monitoring, learning efficiency analysis, and automated recommendations into a single interface. Through this integration, lecturers can simultaneously monitor student achievement, work efficiency, security status, and assessment results in real-time. This comprehensive visualization supports data-driven decision-making and provides a holistic view of the learning evaluation process. The fuzzy performance distribution shows that most students are in the Good and Superior categories, while only a small proportion require additional coaching or review. These findings suggest that the fuzzy logic approach can provide more adaptive and comprehensive evaluations because it considers a combination of academic indicators, learning efficiency, and user behaviour rather than relying solely on final score as the basis for assessment (Papakostas et al., 2023).

In addition, the integrated dashboard provides exam integrity indicators and automated recommendations that support lecturers in monitoring student performance and making data-driven instructional decisions. Unlike conventional score-based ranking that relies solely on quiz scores, the fuzzy model in this study incorporates additional indicators such as integrity behaviour, attempt count, and time ratio. As a result, students with similar quiz scores may receive different performance classifications when differences in examination behaviour are considered. This characteristic enables a more context-aware evaluation process and illustrates the adaptive nature of the fuzzy approach.

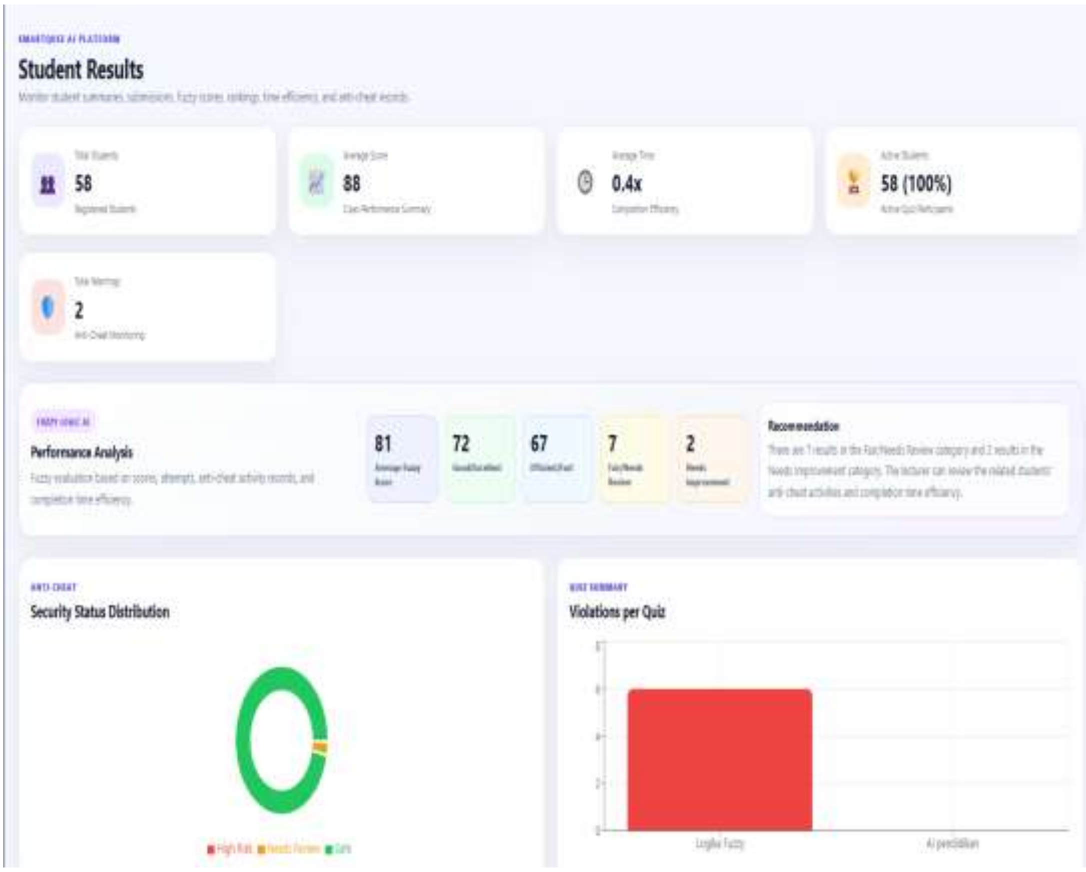

Figure 5. Student Performance and Examination Integrity Analytics Dashboard

The results show that the integration of learning analytics, fuzzy logic, and exam integrity mechanisms is able to produce a more comprehensive higher education learning evaluation compared with conventional approaches that focus only on the final score. The system not only evaluates students' academic achievements, but also considers user behaviuor during the evaluation process. These findings reinforce the research by Özseven and Çağman (2022), who reported that fuzzy logic can produce more adaptive performance evaluations than traditional assessment methods. In this study, the fuzzy approach is not only used to process academic scores, but also integrates exam integrity indicators to produce more objective assessments. In addition, the analytical dashboard in this study is also strengthened in the ability to increase student involvement through the presentation of learning information in real time (Jayashanka et al., 2022). These findings are further supported by Bernacki et al. (2025), who demonstrated that digital traces can be used to understand student learning behavior and development more objectively. Visualization of learning data through an analytical learning dashboard can increase student engagement and support improved learning outcomes (Alam et al., 2023). These findings are further supported by Papakostas et al. (2023), who showed that fuzzy logic is effectively used to model student mastery levels in digital learning environments.

Sajja et al. (2025) emphasized that the integration of AI and learning analytics can support data-driven learning decisions through the use of student behavioral and performance information. The system's ability to integrate performance evaluation and user behaviour monitoring reflects the characteristics of an intelligent assessment system, as demonstrated by Shobana and Kumar (2022), who showed that user interaction data can be leveraged to generate more comprehensive evaluations. Recent developments in intelligent learning systems have moved beyond static score-based measurement toward dynamic and process-oriented analysis that continuously monitors learner activities, performance, and behavioural indicators to support adaptive educational decision-making (Purwandari et al., 2025). Student activity data in a digital learning environments can be used to build a model for predicting academic performance using a learning analytics approach (Tao et al., 2022). The use of analytical learning dashboards helps lecturers focus more on activities and has a positive impact on improving student learning outcomes (Cukurova, 2025). Learning evaluations that integrate various academic indicators and learning technology are able to produce more effective information to support the learning process (Alalawi et al., 2025). The use of learning analytics can help improve student learning success and support data-driven academic decision-making (Šimić et al., 2025).

The analytical results of the question items also show that the system is able to identify items with a high level of difficulty based on the distribution of the correct rate and error rate. This ability provides important information for lecturers to revise questions, improve the quality of evaluation, and improve the learning process at the next meeting. The results of this study are in line with Serrano et al. (2025), who proposed a learning analytics approach at the micro level for assessing knowledge mastery and learning effectiveness. These findings are further reinforced by Banihashem et al. (2025) who stated that effective formative assessment should identify students' current learning status, detect learning difficulties, and provide feedback to support learning goals. In addition, the dominance of the Safe category in risk analysis shows that the monitoring mechanism applied is able to encourage students to take part in the evaluation in a more disciplined manner. Beyond providing feedback, learning analytics can also support early intervention. Susnjak et al. (2022) emphasized that one of the main objectives of learning analytics is the early identification of students at risk so that timely interventions can be implemented. The implications of this study show that the integration of fuzzy logic and learning analytics can be applied as an alternative approach to improve the quality of digital learning evaluation. The system was developed to allow lecturers to obtain information on academic performance, user activity, and the level of risk of violations in one integrated dashboard. The implementation of this system can potentially support data-based learning decision-making in higher education environments. The main contribution of this research lies in the development of a Smart Quiz System that integrates fuzzy Mamdani-based performance evaluation, user behavior monitoring, examination integrity mechanism, and question item analysis in one web-based platform. Unlike previous research, which generally focused only on performance visualization or academic evaluation, the proposed system developed is able to produce performance analysis and exam integrity assessment through an intelligent assessment system.

This study has several limitations. First, the implementation of the system was conducted in only two classes; therefore, the generalizability of the findings still requires further validation. Second, the evaluation model relies on predefined membership functions and fuzzy rules that were developed through prototype testing and internal review. Formal validation by external experts and empirical calibration using larger datasets have not yet been conducted. Furthermore, the proposed fuzzy-based assessment model has not yet been benchmarked against conventional score-based evaluation methods. Therefore, the current classifications should be interpreted as preliminary and require further validation before broader implementation. Third, the user behaviour indicators were limited to activities that could be automatically recorded by the system including tab switching, fullscreen violations, and warning count. Future research could integrate machine learning techniques or adaptive learning analytics to improve the accuracy of performance and examination integrity classification. In addition, testing on a larger number of users, different courses, and multiple institutions is necessary to improve the external validity and generalizability of the proposed system. Future studies may also focus on the development of more sophisticated integrity indicators, such as temporal analysis of user behavior patterns, artificial intelligence-based anomaly detection, and comparative benchmarking against conventional assessment approaches. Therefore, the findings of this study should be interpreted as evidence from a prototype implementation conducted in a single institutional setting, and further validation through comparative benchmarking, external expert review, and larger multi-institutional studies is required before broader adoption.

CONCLUSIONS

This study developed a web-based Smart Quiz System that integrates fuzzy Mamdani-based performance evaluation, exam integrity monitoring, learning analytics dashboards, and question item analytics within a single platform. The system utilized four fuzzy input variables, namely score percent, integrity, attempt count, and time ratio, to generate performance classifications and examination risk levels. In addition, the platform records user activities during the assessment process, enabling lecturers to monitor both academic performance and examination behavior simultaneously. The implementation results from 58 students and 81 recorded quiz attempts showed that the system was able to classify evaluation outcomes into the categories of Superior, Good, Enough, and Needs Coaching, while also identifying examination integrity risks through behavioral monitoring indicators. Furthermore, the integrated dashboard and item analytics features provided useful information for identifying difficult questions, monitoring student activity patterns, and supporting data-driven instructional decision-making. These findings indicate that the integration of fuzzy Mamdani-based performance evaluation, user behavior monitoring, learning analytics, and exam integrity mechanisms within a single platform can provide more comprehensive evaluation information than conventional score-based assessment approaches. From a theoretical perspective, this study extends the application of fuzzy logic in educational evaluation by integrating examination integrity indicators derived from user behavioural data into the fuzzy inference process, enabling a more comprehensive assessment that considers both academic performance and examination behaviour.

Although the proposed system demonstrated its ability to support performance evaluation and examination integrity monitoring, the membership functions and fuzzy rule base remain prototype-based and have not yet undergone formal external validation. Future research should validate the proposed model using larger and more diverse datasets, benchmark its performance against conventional score-based assessment methods, incorporate expert review and empirical calibration, and explore the integration of machine learning techniques, predictive learning analytics, and behavioural anomaly detection to further enhance adaptive evaluation, monitoring, and recommendation capabilities across broader educational contexts.

AUTHOR CONTRIBUTION STATEMENT

IWSN Conceptualization, methodology, backend software development, system design, data collection, formal analysis, visualization, investigation, initial draft writing, and manuscript editing. RMA frontend software development, supervision, methodology review. EAMS academic supervision, interpretation of research results, manuscript review and revision.

AI DISCLOSURE STATEMENT

The authors used ChatGPT to assist with language improvement, manuscript organization, editorial refinement, and literature exploration. All references identified during the writing process were independently reviewed and verified by the authors to ensure their relevance, accuracy, and appropriate use in supporting the claims presented in this manuscript. The authors take full responsibility for the content of this publication.

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