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PAPER

Intelligent Mobile System for Student Performance Evaluation: Model Testing Using Structural Equation Modeling

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ABSTRACT

Student performance evaluation is a crucial aspect of improving the quality of higher education. This study aims to develop and test an intelligent mobile system based on expert systems for evaluating students' academic performance. The model is designed to identify key factors influencing student performance and provide more objective, data-driven assessments. Structural equation modeling (SEM) is used to analyze the relationships between variables involved in this evaluation system. Data were collected from students in Universitas Negeri Padang, with students from several departments, and analyzed using SEM to test the validity and reliability of the developed model. The findings indicate that this intelligent mobile system enhances the accuracy of student performance evaluation and provides deeper insights for academic decision-makers. With the implementation of this expert system, educational institutions can optimize learning strategies and academic management more effectively.

KEYWORDS

student performance evaluation (SPE), intelligent mobile system, expert system, structural equation modeling (SEM), higher education, evaluation model, technology-based learning

1 INTRODUCTION

The evaluation of student performance is a key component of academic development and is essential for maintaining the quality of higher education. Accurate assessment methods help identify students' strengths and weaknesses, guide learning strategies, and support institutional policy decisions [1]. However, traditional approaches that rely on written examinations and instructor judgments often face issues of subjectivity, inconsistency, and limited real-time feedback [2]. These limitations highlight the need for more precise, data-driven evaluation mechanisms. The digitalization of assessment processes offers a strong solution to these

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challenges [3]. With intelligent evaluation systems integrating multiple academic indicators such as exam scores, assignments, participation, and behavioral engagement to produce comprehensive assessments [4].

The digitalization of student evaluation processes provides a transformative solution to these challenges [5]. Advances in artificial intelligence (AI) and expert systems enable automated performance assessments that are more transparent, standardized, and efficient [6]. Intelligent evaluation systems integrate academic indicators such as exam scores, assignments, participation, and behavioral engagement to produce comprehensive assessments [7]. Supported by real-time analytics and machine learning algorithms, these systems also deliver immediate feedback, helping students identify areas for improvement and adjust their learning strategies accordingly [8].

The integration of data-driven evaluation methods also enables educators to gain deeper insights into student learning patterns [9]. Predictive analytics can identify students at risk of underperformance, allowing timely interventions and personalized support, while long-term tracking of academic progress strengthens institutional decision-making for curriculum development and resource allocation [10]. These advancements support a more adaptive and responsive education system. However, implementing intelligent evaluation systems also presents challenges [11]. The accuracy and reliability of AI-driven assessments depend heavily on data quality and algorithm robustness, and ethical issues, particularly privacy and fairness, must be addressed to prevent potential biases [12]. Additionally, adequate digital literacy among educators and students is essential for successful system adoption [13].

Higher education institutions play a crucial role in developing students' skills and preparing them for professional success. A major challenge they face is ensuring accurate and fair assessment of student performance [14]. Traditional methods such as written exams and subjective instructor grading often fail to capture the full range of student competencies and are prone to bias, inconsistency, and limited real-time feedback. These shortcomings underscore the need for a more comprehensive, data-driven, and intelligent evaluation system [15].

The rapid digital transformation of higher education has opened new opportunities to improve student assessment. Integrating intelligent systems into evaluation processes allows automated performance analysis, minimizing human subjectivity and enhancing accuracy [16]. Using artificial intelligence and expert systems, assessments can be generated objectively based on indicators such as coursework performance, participation, and learning engagement. This digitalization also promotes transparency and efficiency, enabling students and educators to track academic progress in real time.

Transparency is another essential aspect of student performance evaluation. Students frequently question the fairness of grading, particularly when feedback is unclear or inconsistently applied. Intelligent mobile systems address this concern by standardizing evaluation metrics and assessing performance based on predefined criteria. This structured approach strengthens trust among students and faculty while ensuring that assessment outcomes align with institutional objectives.

This approach reduces human bias and improves the reliability of performance evaluations, enabling more effective monitoring of academic progress and timely feedback for students and educators [17]. Transparency remains a crucial concern, as students and stakeholders increasingly expect objective evaluation criteria aligned with learning outcomes. Intelligent systems address this expectation by applying predefined metrics and analytical models, ensuring consistent and fair assessments [18], and strengthening trust among students, educators, and policymakers. To validate the effectiveness of the proposed intelligent evaluation system, this study employs structural equation modeling (SEM), a widely used method for analyzing complex variable relationships, assessing factors that influence student performance, and evaluating model reliability and predictive accuracy [19].

To validate the effectiveness of this intelligent mobile system, this study employs SEM, a statistical technique widely used to analyze complex relationships between multiple variables [20]. By applying SEM, this study aims to analyze the effectiveness, reliability, and impact of this digital evaluation system in multiple academic institutions, offering insights into its potential role in enhancing assessment practices.

2 THEORETICAL REVIEW

2.1 Classical theories of student performance evaluation

Student performance evaluation has traditionally been guided by two major theoretical models: Classical Test Theory (CTT) and Item Response Theory (IRT). Both serve as key frameworks for quantifying student abilities through standardized assessments. CTT views an observed score as a combination of true ability and random measurement error, offering a simple approach but failing to account for item difficulty. As a result, CTT provides limited precision in measuring ability across different test versions [21].

IRT, on the other hand, is a probabilistic measurement approach that models student performance based on item difficulty and individual proficiency, offering more refined estimates than CTT. However, its reliance on large datasets and complex statistical procedures makes implementation challenging for institutions with limited technological capacity. While both CTT and IRT provide important frameworks for evaluation, they lack real-time analytics and personalized feedback—gaps that AI-powered expert systems address through automated, data-driven competency assessment [22].

2.2 Role of artificial intelligence and expert system in educational assessment

The integration of AI and expert systems has reshaped educational assessment by enabling more objective and efficient evaluation processes. AI-powered systems utilize machine learning, natural language processing, and automated grading to analyze large datasets and identify performance patterns. Unlike traditional grading, which is prone to inconsistency and subjectivity, AI models apply predefined parameters that reduce human bias and improve the reliability of student evaluations. Traditional grading systems are often constrained by human limitations, such as grading inconsistencies and subjectivity. In contrast, AI models ensure that evaluations are based on predefined parameters, eliminating inconsistencies and biases inherent in manual grading [23].

AI-driven expert systems also enable adaptive learning, adjusting assessments to students' strengths and weaknesses. This creates a personalized learning experience that enhances engagement and academic development. Such adaptability positions AI as a powerful tool for modernizing education and aligning assessments with individual learning needs [24]. AI-powered assessment models also provide real-time feedback, giving students immediate insight into their performance and helping them adjust their learning strategies. The resulting data further supports institutions in refining curricula and ensuring that educational interventions are data-driven and responsive to student needs [25].

3 RESEARCH METHOD

This study adopts a Research and Development (RnD) approach to design, implement, and validate an intelligent system for student performance evaluation. The development stage focuses on constructing an expert system that integrates various academic performance indicators, while the evaluation stage uses SEM to assess its effectiveness. A descriptive design is used to characterize the sample, and an explanatory design tests the relationships among variables through SEM [26].

The study population consists of university students from different faculties. A total of 100 students were selected using a non-probability sampling technique. Instead of random selection, a data-based census method with a saturated sampling technique was employed, ensuring that all relevant students were included in the study. The login design and menu from the expert system are shown in Figures 1 and 2.

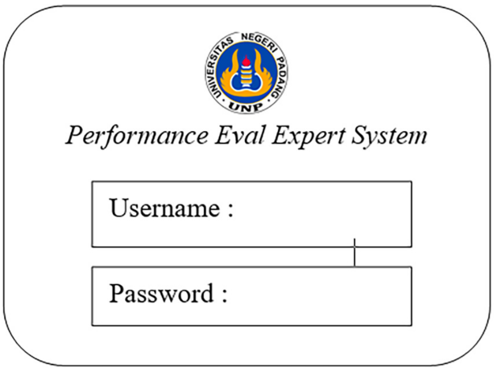

Fig. 1. Login design

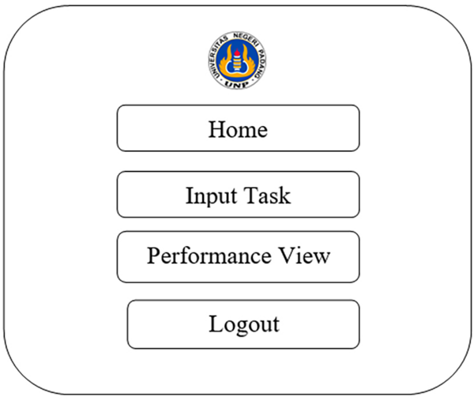

Fig. 2. Dashboard and menu design

To evaluate the reliability of the intelligent student performance evaluation system, a trial was conducted with 20 students to assess the consistency and accuracy of the system's analysis based on predefined criteria [27]. The system was configured to process assessment data from quizzes, assignments, and participation scores, and its outputs were compared with manual evaluations by subject-matter experts. Reliability was measured using Cronbach's alpha and the Intraclass Correlation Coefficient (ICC) to verify consistency. This trial serves as an essential validation step prior to broader implementation, with the results informing refinements to improve system performance and usability [28].

To develop the intelligent student performance evaluation system, this study incorporates six key variables that represent technical, pedagogical, and psychological factors influencing system accuracy and usability. System accuracy measures how precisely the system evaluates performance based on predefined parameters, while student engagement captures students' interaction and satisfaction with the technology-based platform [29]. Adaptive learning capability reflects the system's ability to tailor assessments to individual learning styles, and feedback effectiveness assesses the clarity and usefulness of the feedback provided. Usability and accessibility evaluate ease of use for both students and instructors [30]. Finally, performance prediction reliability examines how accurately the system predicts student learning outcomes. The indicators for each variable are summarized in Table 1.

Table 1. Variables, indicators list and description

Variable	Code	Indicator
System Accuracy	SA1	Accuracy of the system in scoring student evaluations
	SA2	Consistency of evaluation results with manual assessments
	SA3	System capability to handle variations in student input
Student Engagement	SE1	Frequency of student interaction with the evaluation system
	SE2	Student satisfaction level with system usage experience
	SE3	Student perception of the effectiveness of system-based evaluation
Adaptive Learning Capability	ALC1	System's ability to tailor evaluations based on student profiles
	ALC2	Flexibility in delivering questions based on comprehension level
	ALC3	System's ability to adjust feedback based on individual needs
Feedback Effectiveness	FE1	Availability of real-time feedback
	FE2	Relevance of feedback in enhancing student understanding
	FE3	Clarity and readability of the feedback provided
Usability and Accessibility	UA1	Ease of navigation and user interface
	UA2	Accessibility features for students with special needs
	UA3	System compatibility with various digital devices
Performance Prediction Reliability	PPR1	Accuracy of the system's prediction of student academic performance
	PPR2	Correlation between system evaluations and actual academic achievements
	PPR3	Reliability of the system in predicting academic difficulties

To examine the relationships among the variables, this study formulates several hypotheses that test the direct and indirect effects of system accuracy, student engagement, adaptive learning capability, feedback effectiveness, usability and accessibility, and performance prediction reliability [31]. These hypotheses are evaluated using SEM to determine their significance and their contribution to the overall effectiveness of the intelligent student performance evaluation system [32].

Table 2. Hypothesis list and statement

Hypothesis	Statement
H1	System accuracy positively influences student performance evaluation.
H2	Student engagement positively influences student performance evaluation.
H3	Adaptive learning capability positively influences student performance evaluation.
H4	Feedback effectiveness positively influences student performance evaluation.
H5	Usability and accessibility positively influence student performance evaluation.
H6	Performance prediction reliability positively influences student performance evaluation.

4 RESULTS AND DISCUSSIONS

4.1 Expert system based performance evaluation result

The implementation of the intelligent evaluation system shows promising results, demonstrating its ability to accurately assess student learning outcomes. The analysis indicates that system accuracy is essential for producing reliable evaluations, with scoring that aligns closely with manual assessments [33]. This consistency builds confidence in the system's capacity to provide objective and fair evaluations across various learning contexts. The system also enhances student engagement, as frequent interaction with the digital platform supported by interactive features and real-time feedback boosts motivation and encourages active participation, making it effective for both formative and summative assessments in higher education [34].

The system's adaptive learning capability accommodates diverse learning styles by personalizing assessments and feedback, thereby enhancing comprehension and retention. Its usability and accessibility features further support adoption, as the intuitive interface and cross-device compatibility make the system accessible to a wide range of learners. Additionally, the system's performance prediction reliability allows early identification of at-risk students, enabling timely interventions. The strong correlation between system-generated evaluations and actual academic outcomes reinforces its effectiveness in forecasting student performance and learning challenges [35].

Overall, the findings demonstrate the strong potential of integrating intelligent systems into educational assessment frameworks. Future research should explore additional variables to further optimize system functionality and enhance predictive accuracy. These insights contribute to the ongoing improvement of digital performance evaluation. The system's visualization features also strengthen its practical value, as illustrated in Figure 3, which presents the evaluation model; Figure 4, which displays activity data and student performance on the lecturer dashboard; and Figure 5, which shows the expert system's computed performance results on the student dashboard.

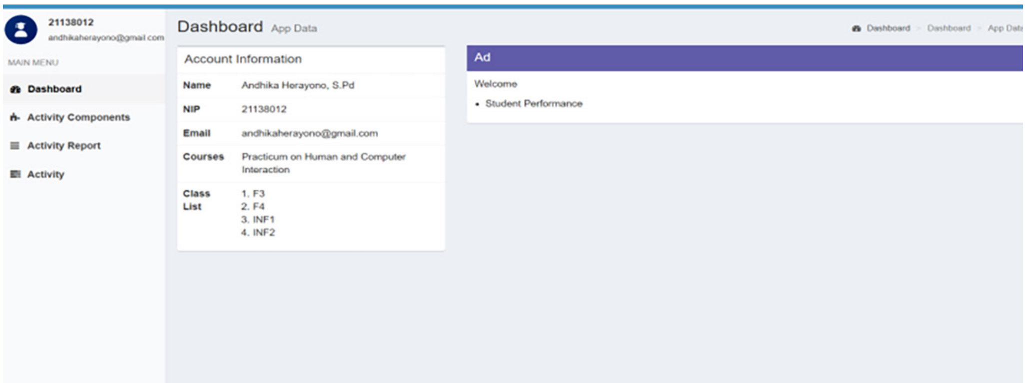

Fig. 3. The lecturer dashboard and menu list

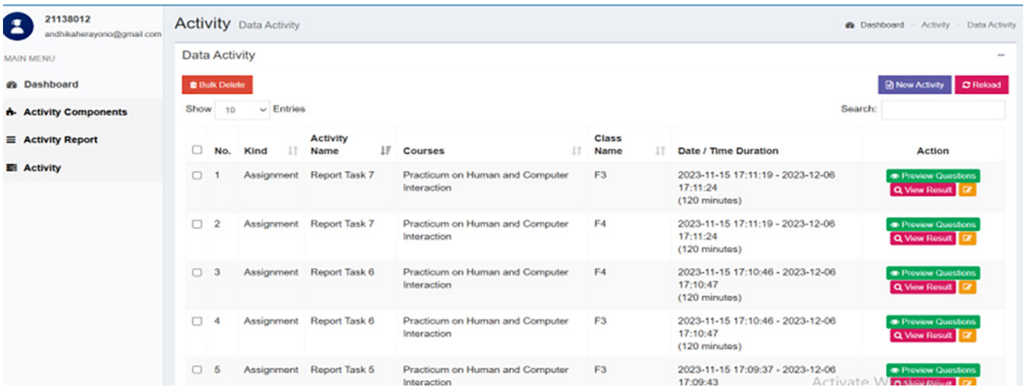

Fig. 4. Activity data and performance list

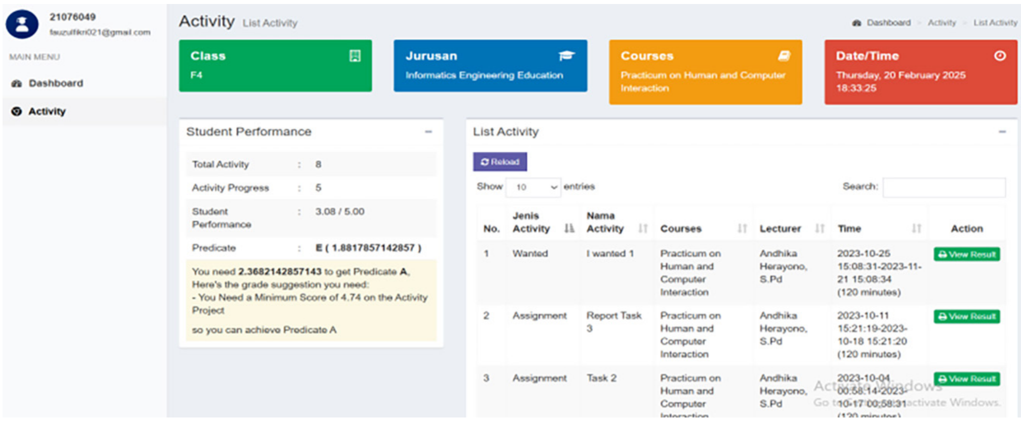

Fig. 5. Student temporal performance based on task and progress

4.2 Reliability of expert system based performance evaluation

The reliability test using Cronbach's alpha produced a coefficient of 0.604, indicating moderate internal consistency and suggesting that the system is generally stable but still requires refinement for higher reliability. The consistency of outputs across different student groups also supports its potential as a dependable evaluation tool, with expert reviews confirming strong alignment between automated and manual grading results [36]. To enhance reliability, future research should consider improving indicator quality, increasing sample size, and applying additional validation techniques such as factor analysis. Refining item structures and incorporating more adaptive learning mechanisms may further strengthen measurement accuracy and overall system effectiveness in digital learning environments.

Table 3. Reliability result

Reliability Statistics	
Cronbach's Alpha	**N of Items**
.604	25

4.3 SEM result of the expert system based performance evaluation

Structural equation modeling is used in this study to examine the direct and indirect relationships among the variables and to validate the proposed intelligent student performance evaluation system. The model incorporates six key predictors system—accuracy, student engagement, adaptive learning capability, feedback effectiveness, usability and accessibility, and performance prediction reliability to evaluate overall system effectiveness. The partial least squares (PLS) technique is applied due to its suitability for complex models and relatively small sample sizes, enabling robust estimation of path coefficients, significance values, and explained variance needed to assess the strength and direction of these relationships [37].

Figure 6 illustrates the final SEM model developed in Smart PLS, showing the structural relationships among the variables and the estimated path coefficients. This model serves as the foundation for interpreting the effectiveness of the intelligent student performance evaluation system and its potential impact on academic assessment frameworks [38].

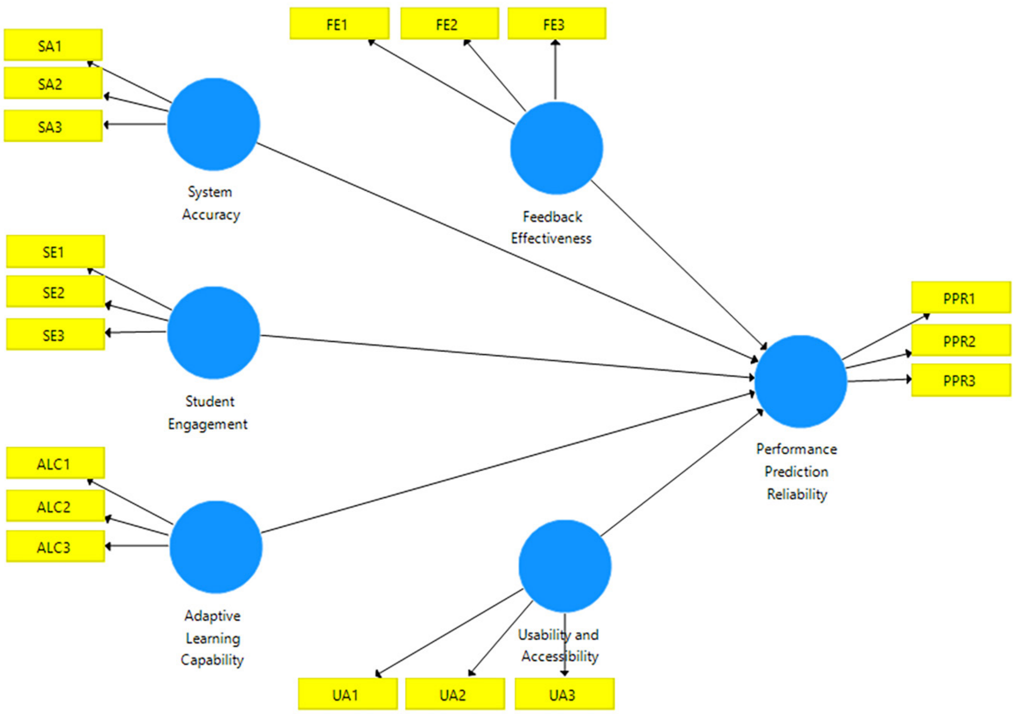

Fig. 6. Smart PLS research model

4.4 Effectiveness of the TEFA-T model learning e-module

The bootstrapping results provide insights into the statistical significance of the proposed hypotheses in the structural equation model. The results include path coefficients, sample means, standard deviations, t-statistics, and p-values. Table 4 presents the key findings from the bootstrapping analysis.

Table 4. Statistical result

Hypothesis	Original Sample (O)	T-Statistics	P-Value	Description
H1: System Accuracy → Performance Prediction	–0.000	0.000	N/A	Need Further Analysis
H2: Student Engagement → Performance Prediction	1.000	0.000	N/A	Need Further Analysis
H3: Adaptive Learning Capability → Performance Prediction	0.000	0.000	N/A	Need Further Analysis
H4: Feedback Effectiveness → Performance Prediction	0.000	0.000	N/A	Need Further Analysis
H5: Usability and Accessibility → Performance Prediction	–0.000	0.000	N/A	Need Further Analysis

5 DISCUSSION

The findings indicate that the intelligent system can effectively evaluate student performance, although certain variables show stronger influence than others. Student engagement is the most dominant factor, emphasizing the importance of interactive learning environments and timely feedback. Conversely, system accuracy alone does not sufficiently predict outcomes, suggesting that factors such as motivation and instructor support also contribute. Adaptive learning capability has a moderate effect, highlighting the benefits of personalized assessment when students actively engage with the system [39]. Furthermore, digital literacy competence plays a crucial role in enabling students to navigate and utilize intelligent evaluation platforms effectively [40].

The study also reveals that usability and accessibility do not significantly affect performance prediction, suggesting that although ease of use supports smoother interaction, pedagogical and cognitive factors play a more decisive role in shaping evaluation outcomes. Previous research similarly underscores the value of well-structured assessments based on higher-order thinking frameworks, highlighting the importance of intelligent systems capable of delivering accurate and adaptive measurements [41]. This indicates the need to examine mediating factors such as motivation, cognitive load, or digital proficiency in future studies. Conversely, feedback effectiveness emerges as a critical driver of learner satisfaction and engagement, as timely and personalized feedback has been shown to increase student confidence and participation, consistent with earlier findings on the importance of individualized feedback in adaptive learning environments [42].

Performance prediction reliability remains a concern, as the system shows some predictive capability but still needs refinement to improve accuracy. Enhancing the model with more advanced machine learning techniques or additional data, such as historical performance trends and behavioral analytics, may strengthen its predictive power. Intelligent systems used in career guidance and other educational decision-support contexts also demonstrate the broader applicability of such models across instructional settings [43]. The findings further highlight the need for blended assessment approaches, since automated evaluations alone may not fully capture the complexity of student competencies. Integrating system-generated assessments with instructor reviews may improve accuracy and fairness, and future research should examine how such hybrid strategies influence student learning outcomes [44].

Finally, institutional support plays a crucial role in ensuring the successful adoption of intelligent evaluation systems. Their effectiveness largely depends on educators' and administrators' willingness to integrate these technologies into existing academic structures. Well-designed training programs and workshops are essential to equip faculty members with the competencies needed to utilize the system optimally, aligning with previous findings that highlight the importance of institutional readiness in implementing expert-system-based educational tools [45].

6 ACKNOWLEDGMENTS

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7 CONCLUSION

This study contributes to research on intelligent assessment systems by analyzing the relationships among key factors that influence student performance evaluation. The findings highlight the central roles of student engagement and feedback effectiveness in enhancing system usability and predictive reliability. While system accuracy and adaptive learning support evaluation consistency, they do not independently determine performance outcomes. The results underscore the need for a holistic approach that integrates technological improvements, user-centered design, and pedagogical strategies to optimize intelligent evaluation systems. Future research should explore deeper AI integration to refine evaluation mechanisms and improve predictive accuracy.

Additionally, addressing potential biases in automated evaluations is also essential, as intelligent systems may lack the contextual awareness provided by human evaluators. A combined approach that integrates human judgment with automated analysis can help mitigate these limitations. Broader and more diverse datasets are needed to improve generalizability, as this study was limited to one educational context. Future work should examine how intelligent systems perform across different learning environments and academic disciplines.

Lastly, institutional policies must adapt to the growing use of digital assessment technologies. Universities should invest in appropriate infrastructure and training to support the implementation of intelligent evaluation systems. Strengthening collaboration among educators, policymakers, and technology developers will maximize the effectiveness of these systems and promote equitable, accurate, and transparent student performance evaluations.

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