Zero : Jurnal Sains, Matematika, dan Terapan
E-ISSN : 2580-5754; P-ISSN : 2580-569X
Volume 9, Number 3, 2025
DOI: 10.30829/zero.v9i3.27041
Page: 950 - 958

Fuzzy-AHP for Teaching Quality Assessment and Student Performance Prediction in Mathematics Education Program

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Article Info

Article history:

Accepted 26 December 2025

Keywords:

Alumni satisfaction;
Area under the curve (AUC);
Classification and regression tree (CART);
Integrity zone;
Service quality.

ABSTRACT

This study proposes a fuzzy–Analytic Hierarchy Process (Fuzzy-AHP) model to evaluate teaching quality and predict student academic performance in a Mathematics Education program, based on data collected from 100 undergraduate Mathematics Education students ($n = 100$). A structured Evaluation Index System (EIS) comprising six criteria and twenty-six sub-criteria was constructed, with criterion weights derived using AHP based on expert judgments and student responses represented as triangular fuzzy numbers. The model produces composite teaching quality scores through fuzzy aggregation and centroid defuzzification, identifying Integration and Relevance of Teaching as the most influential dimension. Predictive validation using Spearman correlation and linear regression confirms a significant positive relationship between teaching quality and academic performance ($\rho = 0.46$, $p < .01$), with instructional quality explaining 21% of performance variance. From an applied mathematics perspective, this study contributes a formally structured fuzzy-AHP modelling framework with empirical predictive validation, advancing teaching quality assessment beyond descriptive ranking toward evidence-based performance prediction.

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1. INTRODUCTION

Higher education institutions are encountering increasingly complex strategic challenges, including low graduation rates, escalating curricular demands, and intensifying accreditation and quality assurance pressures that mandate greater transparency and accountability. These challenges extend beyond administrative concerns; if unresolved, they risk undermining the core educational processes—manifesting in misalignment between instructional practices and learning outcomes, the development of policies lacking empirical grounding, and insufficient feedback mechanisms that hinder instructors' pedagogical improvement. This condition highlights that teaching quality is not merely a supportive component but a critical determinant of student academic success and institutional standing.

Despite the recognized importance of teaching quality in higher education, existing evaluation systems remain largely subjective and offer limited diagnostic value, particularly when they rely primarily on student-generated assessments [1][2]. This reliance creates a mismatch between the demand for rigorous, evidence-based evaluation and the capabilities of current instruments to capture the multidimensional nature of instructional quality. As a result, there is a clear need for an evaluative framework that systematically integrates qualitative judgments with quantitative analysis. Such an approach has the potential to reduce subjectivity, enhance interpretability, and support more actionable decision-making in teaching quality assessment, thereby contributing to institutional quality assurance and academic excellence [3][4].

The primary goal of learning at all levels of education is to bring about fundamental changes in learners. To facilitate the transmission of knowledge, educators must apply appropriate teaching methods that align with specific objectives and intended graduate outcomes. In traditional settings, many practitioners have widely adopted teacher-centered approaches to deliver instruction, rather than student-centered methods. To this day, questions regarding the effectiveness of teaching methods on student learning continue to generate significant interest within educational research [5]. In reality, low academic performance among students is often closely associated with the use of ineffective teaching methods in delivering knowledge. Substantial research on the effectiveness of instructional approaches indicates that teaching quality is frequently reflected in student achievement. [6] Teaching is a process aimed at producing desirable changes in learners in order to achieve specific outcomes. For instructional methods to be effective, educators must master a range of teaching strategies that take into account the level of complexity of the concepts being taught [7][8]

The multifaceted nature of teaching quality, influenced by variables such as classroom performance, coherence in instructional design, and the subtleties of the learning experience, necessitates a more holistic approach [9]. An effective evaluation system must encompass comprehensive indicators, addressing not only the final outcomes but also the learning process itself [10][11]. Conventional evaluation methods tend to be subjective and are often inadequate in capturing the uncertainties or ambiguities present in students' evaluations of lecturers. One such approach is the Fuzzy Analytical Hierarchy Process (Fuzzy-AHP), which combines the Analytical Hierarchy Process (AHP) with fuzzy logic to yield more accurate and realistic assessments [12][13][14][15]. Fuzzy Logic and the Analytic Hierarchy Process (AHP) are widely recognized methodologies employed to tackle the complexities inherent in multi-criteria evaluation [16][17]. While AHP assists in determining the relative weights of various criteria, fuzzy logic facilitates the transformation of linguistic assessments into numerical data suitable for quantitative analysis.

The integration of these methodologies has demonstrated effectiveness in designing flexible evaluation models that more accurately reflect real-world conditions. The integration of Fuzzy Logic and the Analytic Hierarchy Process (AHP) has become a common approach for addressing the complexity of multi-criteria evaluation, including in assessments of teaching quality. Although these methods offer a more flexible framework that accommodates subjectivity, prior Fuzzy-AHP studies exhibit notable limitations. Most research has focused solely on constructing indicator systems or ranking instructors, without examining whether the assessed dimensions of teaching quality bear any empirical relationship to student learning outcomes. The absence of predictive validity creates a critical gap in the literature, as existing models do not clarify the extent to which evaluated teaching attributes genuinely contribute to academic achievement. [18][15][19].

To address this gap, the present study develops a Fuzzy-AHP model that not only provides a structured evaluation of teaching quality but also analyzes the statistical relationship between teaching indicators and student academic performance in the Mathematics Education program. This approach shifts evaluation practices from perception-based rankings to evidence-based assessments with direct implications for improving instructional quality. By offering a more objective, adaptive, and empirically validated model, this study makes a substantial contribution to quality assurance practices and data-informed decision-making in higher education [20][10]. Therefore, the objectives of this research are to develop a Fuzzy-AHP model for assessing the quality of lecturers' teaching and to analyze the relationship between teaching quality and students' academic achievement in the Mathematics Education program. Through this approach, it is anticipated that educational institutions will be equipped with a more objective and adaptive tool to evaluate and enhance the teaching and learning process.

2. RESEARCH METHOD

2.1 Contruction the Evaluation Model

The evaluation framework was constructed as a hierarchical multi-criteria decision model consisting of six main criteria and twenty-six sub-criteria. The structure was adapted from the Evaluation Index System (EIS) proposed by Li [23] and refined to reflect the instructional characteristics of a Mathematics Education program. The resulting hierarchy captures both instructional processes and learning outcomes, enabling a comprehensive representation of teaching quality within a formal decision-analytic structure. The evaluation system consists of 6 criterion indicators and 26 sub-criterion indicators, as presented in Figure 1.

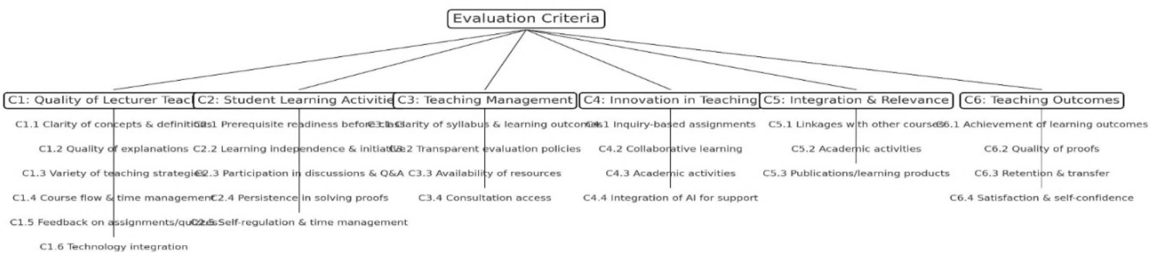

Figure 1. The Criteria and Sub-criteria for Evaluation Teaching Quality

2.2 Analytic Hierarchy Process (AHP) Weight Determination

Criterion and sub-criterion weights were determined using the classical Analytic Hierarchy Process (AHP). A panel of five experts—comprising senior lecturers in mathematics education and academic quality assurance—was involved in the pairwise comparison process. Each expert independently constructed pairwise comparison matrices using Saaty's 1–9 scale.

Individual judgment matrices were aggregated using the geometric mean method, producing a group comparison matrix for each hierarchy level. Priority vectors were computed using the principal eigenvector method, consistent with Saaty's original formulation. Consistency was evaluated using the Consistency Ratio (CR), defined as:

$$CR = \frac{CI}{RI},\ CI = \frac{\lambda_{maks}-n}{n-1} \tag{1}$$

Where λ_{maks} is the maximum eigenvalue and n is the matrix order. A threshold of $\mathrm{CR} < 0.10\mathrm{CR} < 0.10\mathrm{CR} < 0.10\mathrm{CR} \geq 0.10$, experts were requested to revise their judgments until acceptable consistency was achieved. All final matrices satisfied the consistency requirement, ensuring the reliability of the derived weights.

2.3 Fuzzy Representation of Student Evaluations

Student perceptions were collected using a five-point linguistic scale, which was mapped to Triangular Fuzzy Numbers (TFNs) following a standard formulation:

Very Low = (1,1,2), Low = (1,2,3), Moderate = (2,3,4), High = (3,4,5), Very High = (4,5,5).

This TFN scale was adopted without modification to maintain comparability with existing Fuzzy-AHP literature. Thus, the novelty of the present study does not lie in redefining the fuzzy scale, but in the integration of fuzzy evaluation outputs with predictive statistical validation.

2.4 Aggregation of Fuzzy Evaluations

Let $\tilde{x}_{ijk} = (l_{ijk}, m_{ijk}, u_{ijk})$ denote the TFN provided by respondent k for sub-criterion j under criterion i. The aggregated fuzzy evaluation for each indicator was computed as:

$$\bar{x}_j = \left(\frac{1}{n}\sum_{k=1}^{n} a_{jk}, \frac{1}{n}\sum_{k=1}^{n} m_{jk}, \frac{1}{n}\sum_{k=1}^{n} b_{jk}\right) \tag{2}$$

where:

$\bar{x}_j$: the **aggregated Triangular Fuzzy Number (TFN)** for the *j*-th criterion or sub-criterion, representing the collective assessment of all respondents.
j: index of the evaluation criterion or sub-criterion (*j=1,2,…,J*)
k : index of the respondent (*k=1,2,…,n*).
n : total number of respondents.
a_{jk}: **lower bound value** of the TFN provided by respondent *k* for criterion *j*.
m_{jk} : **most likely (modal) value** of the TFN provided by *k* for criterion *j*.
b_{jk}: **upper bound value** of the TFN provided by respondent *k* for criterion *j*.

This averaging process produced a composite fuzzy value that reflects the collective perception of all respondents for each indicator [24][25]. This aggregation operator corresponds to the arithmetic mean of TFNs and ensures mathematical consistency and interpretability.

2.5 Integration of AHP Weights and Fuzzy Scores

The aggregated TFNs were multiplied by their corresponding AHP weights to obtain weighted fuzzy scores:

$$\tilde{S}_{ij} = w_{ij} \otimes \tilde{X}_{ij} \tag{3}$$

where w_{ij} denotes the normalized AHP weight of sub-criterion jjj under criterion iii. Composite fuzzy scores for each main criterion were obtained by summing the weighted TFNs of their sub-criteria.

2.6 Defuzzification and Construction of the Instructional Quality Index

Defuzzification was performed using the **centroid (center-of-area) method**, defined as:

$$D(\tilde{S})\frac{l+m+u}{3} \tag{4}$$

where l, m, u represents the lower, modal, and upper bounds of the TFN. The resulting crisp values were normalized and combined into a single **Instructional Quality Index (IQI)**, computed as the weighted sum of defuzzified criterion scores. This scalar index represents overall teaching quality and serves as the primary explanatory variable in subsequent statistical analysis.

2.7 Validation and Predictive Modelling

To examine predictive validity, the Instructional Quality Index was analyzed in relation to student academic performance. Spearman correlation was employed to assess monotonic association, while simple linear regression was used to evaluate explanatory power. Measurement error inherent in fuzzy evaluations was mitigated through aggregation across respondents and defuzzification prior to statistical modelling.

2.8 Sample Size and Robustness Considerations

The study involved **100 student respondents**, exceeding standard recommendations for stable fuzzy aggregation and correlation analysis. Given the ratio between respondents and evaluation indicators (100:26), the sample size is adequate to support reliable estimation. Additionally, the consistency of expert judgments (CR < 0.10) and convergence of fuzzy aggregation suggest robustness of the resulting indices.

2.9 Statistical Analysis

To examine the relationship between instructional quality and academic performance, the following analyses were conducted by Pearson or Spearman correlation and Simple linier regression modelling. All analyses were performed using statistical SPSS software.[26][27]

3. RESULT AND ANALYSIS

3.1 Results of Teaching Quality Evaluation

Teaching quality is the ability of lecturers to deliver material effectively so that students are able to understand and apply the material. Based on the 6 predetermined teaching quality criteria, the AHP weights obtained are as shown in the following table:

Table 1. Weight of Criteria and Sub-criteria

Criteria	Weight	Sub Criteria	Weight
C1 : Quality of Lecturer teaching	0.33	C1.1 Clarity of concepts and definitions	0.20
		C1.2 Quality of explanations	0.22
		C1.3 Variety of teaching strategies	0.16
		C1.4 Course flow & time management	0.16
		C1.5 Feedback on assignments/quizzes	0.13
		C1.6 Technology integration	0.13
C2: Student Learning Activities	0.15	C2.1 Prerequisite readiness before class	0.18
		C2.2 Learning independence & initiative	0.22
		C2.3 Participation in discussions & Q&A	0.22
		C2.4 Persistence in solving proofs & rigorous exercises	0.20
		C2.5 Self-regulation & time management	0.18
C3: Teaching Management	0.07	C3.1 Clarity of syllabus (RPS) & learning outcomes (CPL)	0.30
		C3.2 Transparent evaluation policies (rubrics, weighting)).	0.28
		C3.3 Availability of resources (question bank, proof examples, task archives)	0.22
		C3.4 Consultation access (office hours, online forums)	0.20
C4: Innovation in Teaching	0.04	C4.1 Inquiry-based assignments / proof-writing clinic	0.28
		C4.2 Collaborative learning (peer review of proofs)	0.26
		C4.3 Academic activities (mini-seminars, reading groups)	0.24
		C4.4 Integration of AI for learning support (not for cheating)	0.22
C5: Integration & Relevance of Teaching	0.26	C5.1 Linkages with other courses	0.45
		C5.2 Academic activities (mini-seminars, reading groups)	0.30
		C5.3 Publications/learning products (collaborative lecture notes, OER	0.25
C6: Teaching Outcomes	0.14	C6.1 Achievement of learning outcomes (exam scores, proof	0.35
		assignments	0.30
		C6.2 Quality of proofs (4-level rubric: accuracy, completeness of	
		reasoning, logical structure, notation)	0.20
		C6.3 Retention & transfer (new/isomorphic problems in post-tests)	0.15
		C6.4 Satisfaction & academic self-confidence	

Based on the calculated weight results, the Consistency Ratio (CR) value obtained is < 0.1, so it can be concluded that the comparison results of the importance levels of each criterion and sub-criterion are correct according to Saaty's rules in applying the AHP method.

3.2 Teaching Quality Evaluation for Fuzzy AHP Method

The calculation process for the Fuzzy AHP method can be seen from the results of the normalized AHP criteria and sub-criteria weight ranking. These weights are then converted into defuzzification weights by finding the values in the LMU Table 2, resulting in the defuzzification weight ranking

Table 2. Defuzzification Score of Criteria and Sub-criteria

Criteria	Sub Criteria	Defuzzification Score	Criteria	Sub Criteria	Defuzzification Score
C1	C1.1	0.8	C3	C3.1	0.72
	C1.2	0.75		C3.2	0.74
	C1.3	0.78		C3.3	0.7
	C1.4	0.79		C3.4	0.73
	C1.5	0.76	C4	C4.1	0.68
	C1.6	0.82		C4.2	0.67
C2	C2.1	0.65		C4.3	0.69
	C2.2	0.68		C4.4	0.66
	C2.3	0.7	C5	C5.1	0.6
	C2.4	0.66		C5.2	0.62
	C2.5	0.64		C5.3	0.59
			C6	C6.1	0.72

The lecturer's teaching is central to the quality of learning—especially the clarity of concepts, explanation methods, and teaching strategies. The relevance and connectivity of the material (C5) have a significant impact, indicating an expectation of non-isolated learning. Student activities and learning outcomes are in the middle range, indicating a balanced assessment between input, process, and output. Learning innovation (C4) has the smallest weight, indicating that innovation is valued but not as highly as the basic quality of teaching.

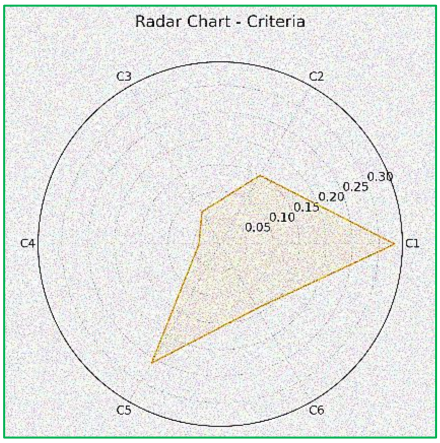

Figure 2. Radar Chart of Defuzzification Criteria

The analysis indicates that Integration and Relevance of Teaching (C5) emerges as the most influential criterion, combining a relatively high weight with the highest defuzzification score, suggesting that the alignment of course content with broader academic activities and curricular relevance is strongly realized. Quality of Lecturer Teaching (C1) also shows a substantial contribution due to its dominant weighting, although its moderate performance implies that incremental improvements in instructional clarity and delivery could produce meaningful system-level impact. Teaching Outcomes (C6) and Student Learning Activities (C2) demonstrate moderate contributions, reflecting satisfactory levels of student achievement and engagement without yet becoming key drivers of overall effectiveness. In contrast, Teaching Management (C3) and Innovation in Teaching (C4) display positive performance but limited influence, constrained primarily by lower priority weighting rather than inadequate implementation, indicating that these dimensions are functioning well but have not been positioned as strategic focal points within the current evaluation framework.

Table 3. Contribution Score Ranking of Criteria

Criteria	Weight	Defuzzyfication	Contribution
C1 : Quality of Lecturer teaching	0.33	0.1734	0.057222
C2: Student Learning Activities	0.15	0.2016	0.03024
C3: Teaching Management	0.07	0.2568	0.017976
C4: Innovation in Teaching	0.04	0.252	0.01008
C5: Integration & Relevance of Teaching	0.26	0.355	0.0923
C6: Teaching Outcomes	0.14	0.275	0.0385

Table 3 shows the most influential sub-criteria are those related to relevance, learning outcomes, and the quality of rigorous thinking skills. Learning planning (RPS, CPL) and evidence-based innovation also hold a significant position. The technology and feedback aspects are at the lowest position, indicating that both are considered less of a priority compared to the core academic aspects. Visually, the radar chart shows a healthy imbalance: a strong focus on core academic quality and outcomes, with support for processes and innovation.

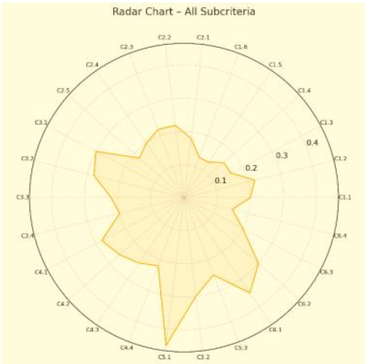

Figure 3. Radar Chart of Defuzzification Sub Criteria

3.3 Mathematic Education Student Performance

Academic achievement is not only measured by grades or GPA, but also includes aspects such as mastery of course material, analytical ability, critical thinking skills, and students' contribution to the academic environment. The questionnaire was distributed to 100 active third-semester students in the Mathematics Education Department, containing 20 statement items related to student performance during the learning process. Based on fuzzy logic analysis, the resulting weights are presented in the following Table 4 sponsiveness, and transparency remain critical determinants of satisfaction in higher education [21], [22], [23].

Table 4. Defuzzification Score of Academic Performance Questinnaire

Question	L	M	U	Defuzzification	Question	L	M	U	Defuzzification
1	3.08	4.08	4.87	4.01	11	2.31	3.26	4.18	3.25
2	3.18	4.15	4.82	4.05	12	3.28	4.26	4.77	4.10
3	3.10	4.08	4.74	3.97	13	2.90	3.90	4.72	3.84
4	3.38	4.36	4.82	4.19	14	2.90	3.87	4.59	3.79
5	3.18	4.15	4.82	4.05	15	2.97	3.95	4.64	3.85
6	2.69	3.67	4.54	3.63	16	2.97	3.97	4.72	3.89
7	2.77	3.77	4.62	3.72	17	2.36	3.36	4.26	3.32
8	3.08	4.05	4.69	3.94	18	2.49	3.49	4.38	3.45
9	2.36	3.36	4.28	3.33	19	3.33	4.33	4.90	4.19
10	2.67	3.67	4.49	3.61	20	3.31	4.28	4.77	4.12

The defuzzification chart shows variations in students' perceptions across the questionnaire statements. The highest scores (≈ 4.1–4.2) indicate very strong satisfaction, particularly in study routines, clarity of assessment, and the relevance of examples, reflecting that learning management and delivery are already optimal. Most statements fall within the middle range (≈ 3.7–4.0), suggesting that the teaching quality is viewed positively, although improvements are still needed in content depth and consistency of explanation. Meanwhile, the lowest scores (≈ 3.2–3.4) appear in areas related to students' confidence in constructing proofs and participation in discussions, indicating the need for additional support through gradual practice and strengthened academic engagement.

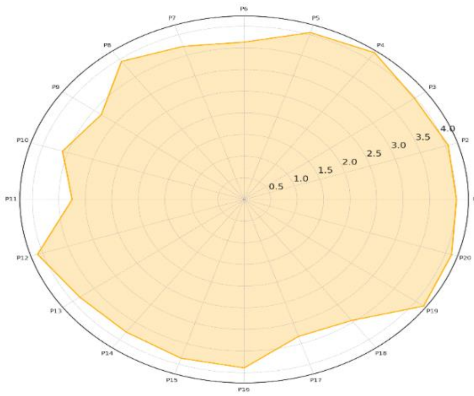

Figure 4. Radar Chart of Academic Performance

3.4 Statistic Analysis

Based on the correlation analysis between instructional quality scores and students' academic performance, the Spearman coefficient showed a **positive and statistically significant relationship (ρ = 0.46, $p < .01$)**. This indicates that higher perceived. The regression analysis demonstrated that instructional quality significantly predicted academic performance (R^2 = **0.21**, $F(1,98)$ = **20.45**, $p < .001$). The regression coefficient was **β = 0.38**, indicating that for every one-unit increase in instructional quality score, student performance increased by **0.38 points** on average. [27] Teaching quality contributes meaningfully to students' academic outcomes, although additional factors beyond instructional quality also influence performance.

3.5 Discussion

The results of this study demonstrate that instructional quality is a multidimensional construct in which curricular relevance and instructional delivery play central roles. The Fuzzy-AHP analysis indicates that Integration and Relevance of Teaching and Quality of Lecturer Teaching exert the strongest influence on overall teaching effectiveness, highlighting the importance of aligning course content with broader academic contexts and ensuring clarity in explanation and instructional flow [21]. The moderate contributions of Student Learning Activities and Teaching Outcomes suggest that while students are generally engaged and achieving satisfactory results, higher-order competencies—particularly independent proof construction and active academic participation—remain areas that require targeted instructional support [28][29].

Furthermore, the statistical findings reinforce the practical significance of teaching quality in shaping academic performance. The positive and significant correlation, along with the regression results, confirms that improvements in instructional quality are associated with measurable gains in student achievement, although instructional factors do not fully account for performance variance. This indicates that teaching quality functions as a key, but not exclusive, determinant of learning outcomes. Collectively, these findings suggest that systematic, data-driven evaluation models such as Fuzzy-AHP can support more objective instructional assessment and inform targeted improvements, particularly in enhancing instructional clarity, relevance, and structured student engagement [30].

4. CONCLUSION

This study establishes a Fuzzy–Analytical Hierarchy Process (Fuzzy-AHP)–based evaluation and prediction framework in which a formally defined instructional quality index is constructed from expert-derived AHP weights and student-based fuzzy assessments. Quantitatively, the model identifies Integration and Relevance of Teaching and Quality of Lecturer Teaching as the dominant contributors, and predictive validation confirms that the resulting index explains 21% of the variance in student academic performance (R^2 = 0.21). The principal methodological contribution lies in extending standard Fuzzy-AHP applications from descriptive ranking to an empirically validated decision-analytic model through the integration of defuzzified composite scores with correlation and regression analysis. This modelling framework reduces subjectivity while enabling direct performance prediction, thereby offering a reproducible and analytically grounded approach suitable for applied mathematics and educational analytics. Practically, the results indicate that improvements in curricular alignment and instructional clarity yield the highest marginal impact on learning outcomes, providing a focused basis for evidence-based quality assurance.

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