GRADEMATE AI: AI-POWERED EDUCATIONAL ASSESSMENT AND LEARNING-GAP DIAGNOSTIC SYSTEM

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ABSTRACT
Digital assessment has become an important component of contemporary education, enabling institutions to conduct examinations, quizzes, assignments, and continuous evaluations through software-based platforms. Although these systems can efficiently produce marks and grades, an overall score does not necessarily explain the concepts that a learner has understood or the areas in which further learning is required. This paper presents GRADEMATE AI, an AI-powered educational assessment and learning-gap diagnostic system designed to provide a more detailed interpretation of student assessment performance. The proposed system evaluates student responses, associates assessment items with relevant learning concepts, analyses performance at the topic level, and identifies potential areas requiring additional attention. The diagnostic information is subsequently used to generate personalized feedback and learning guidance. The proposed framework separates response evaluation from learning-gap diagnosis, allowing assessment results to be transformed into concept-oriented information rather than being represented solely through an aggregate score. The system is intended to support students in understanding their individual learning requirements while providing educators with structured information about areas of difficulty. The paper describes the system architecture, assessment workflow, topic-level performance analysis, learning-gap diagnosis, AI-assisted feedback generation, and evaluation framework. The proposed approach provides a practical foundation for integrating artificial intelligence and learning analytics into educational assessment while retaining the role of human educators in interpreting consequential learning decisions.

Keywords— Artificial Intelligence, Educational Assessment, Learning Analytics, Learning-Gap Detection, Personalized Learning, Student Performance Analysis, Intelligent Assessment, AI in Education.

INTRODUCTION

- Assessment plays a central role in education by providing evidence about a learner's progress, understanding, and achievement. With the growth of digital learning environments, assessments are increasingly conducted through online platforms that can automatically record responses and calculate performance. These systems reduce the administrative effort associated with examination processing and make assessment information available in a structured digital form.
- However, the availability of an assessment score does not necessarily provide a complete representation of student learning. A student may receive a percentage or grade without knowing which concepts contributed to incorrect responses. For example, two learners can obtain a similar overall score while experiencing difficulty with completely different topics. An aggregate result therefore provides limited information when the objective is to determine what each learner should study next.
- This distinction becomes particularly important in assessments containing questions from several learning concepts. An incorrect response to one question may represent an isolated error, whereas repeated errors across questions associated with the same concept may

indicate a broader learning difficulty. Identifying this distinction manually across multiple assessments can require substantial effort from educators.

- Artificial intelligence and learning analytics provide mechanisms for processing educational data at a more detailed level. Recent research reviews show that AI in education spans areas such as adaptive learning, personalized tutoring, intelligent assessment, prediction, and educational analytics. Research on knowledge tracing similarly focuses on estimating a learner's mastery of concepts from historical interactions and assessment behaviour.
- AI-assisted assessment also introduces new challenges. Automated evaluation of free-text responses, for example, is substantially more complex than evaluating predefined answers because students can express the same idea using different language. Research on machine-learning approaches to student free-text evaluation identifies automated assessment and immediate feedback as active research areas while noting the complexity of evaluating open-ended responses.
- These developments indicate that an educational assessment system should not treat artificial intelligence simply as a replacement for conventional grading. Instead, AI can be used as an additional analytical layer that connects assessment evidence with meaningful learning information. Human-centred research in learning analytics and AI in education emphasizes the importance of stakeholder involvement, reliability, trustworthiness, and an appropriate balance between human control and automation.
- To address this requirement, **GRADEMATE AI** is proposed as an AI-powered educational assessment and learning-gap diagnostic system. The system is designed to process assessment responses, associate questions with learning concepts, calculate topic-level performance, identify potential learning gaps, and generate personalized feedback.

The main contributions of the proposed system are:

1. **Automated assessment analysis:** Student responses are processed through a structured evaluation workflow.
2. **Concept-oriented performance analysis:** Question-level outcomes are associated with their corresponding learning topics.
3. **Learning-gap diagnosis:** Topic-level performance is analysed to identify areas that may require additional learning support.
4. **Personalized feedback generation:** Diagnostic information is used to provide feedback relevant to the learner's observed performance.
5. **Integrated assessment workflow:** Response evaluation, topic analysis, diagnosis, and feedback are combined within a single framework.
6. **Human-centred educational support:** The system is designed as a decision-support mechanism rather than as an independent replacement for educator judgment.

The remainder of this paper is organized as follows. Section II reviews relevant research in AI-assisted education, automated assessment, learning analytics, and knowledge tracing. Section III describes the proposed GRADEMATE AI methodology. Section IV presents the evaluation framework and results. Section V discusses limitations and practical considerations. Section VI describes future development opportunities, followed by the conclusion and references.

LITERATURE SURVEY

A. Artificial Intelligence in Education

Artificial intelligence in education has developed into a broad research area covering personalized learning, intelligent tutoring, assessment, prediction, learning analytics, and educational management. A large-scale systematic review by Wang et al. analysed more than two thousand research articles and identified adaptive learning, personalized tutoring, intelligent assessment, profiling, and prediction among the major application areas of AI in education. The review also identified research gaps associated with implementation, methodology, and the practical use of AI systems.

Earlier systematic work by Zawacki-Richter et al. similarly examined AI applications in higher education and identified several application categories involving assessment, prediction, personalization, and intelligent

systems. Their work also emphasized the importance of considering the role of educators rather than treating AI implementation solely as a technical problem.

These studies establish the broader relevance of AI-based educational systems but do not by themselves provide a complete workflow for converting individual assessment responses into topic-specific learning-gap information.

B. Automated Educational Assessment

Automated assessment has been investigated as a means of reducing repetitive evaluation tasks and providing faster feedback to learners. The complexity of automated assessment depends strongly on the question format.

Multiple-choice and other predefined-response questions can generally be evaluated using deterministic rules. Free-text responses present a more difficult problem because the possible answer space is not fixed. Bai and Stede reviewed machine-learning approaches for evaluating student free-text responses and described the use of feature-based, neural, and natural-language-processing methods for automated evaluation.

Research on emerging technologies in assessment and feedback has also identified artificial intelligence and learning analytics as important areas of development in educational assessment. A systematic review reported substantial research activity around AI-supported assessment and feedback while identifying the need for continued investigation of learning outcomes, usability, and human-centred implementation.

C. Learning Analytics and Student Performance

Learning analytics focuses on the collection and interpretation of learner-generated data to support educational decisions. AI-driven learning analytics can analyse information from multiple sources and provide instructors with actionable information. Recent systematic research highlights the importance of connecting analytical tools with educational theory and meaningful instructional use.

However, learning analytics should not be interpreted as automatically equivalent to learning improvement. The usefulness of an analytical result depends on the quality of the underlying data, the interpretation of the output, and the way the information is incorporated into the educational process.

GRADEMATE AI uses this principle by treating assessment analysis as an intermediate stage rather than the final objective. The purpose of the analysis is to transform assessment observations into information about topics requiring further attention.

D. Knowledge Tracing and Concept Mastery

Knowledge tracing represents another important research direction related to learning-gap diagnosis. Knowledge-tracing approaches attempt to estimate a learner's knowledge state or mastery of concepts from historical learning interactions and assessment responses. Surveys of deep-learning-based knowledge tracing describe the field as a method for modelling student concept mastery and predicting future performance.

GRADEMATE AI does not claim to implement a full knowledge-tracing model unless such a model is actually included in the implementation. Instead, the proposed system uses topic-level assessment performance as an initial diagnostic representation. This distinction is important because a single assessment result cannot necessarily represent a student's complete or permanent mastery of a concept.

E. AI-Assisted Feedback

Feedback is an important component of assessment because it provides information that can guide subsequent learning. AI-based systems can potentially generate feedback rapidly and adapt explanations to learner-specific information. Recent systematic research

on AI-supported teaching, learning, and assessment reports applications involving automated feedback, adaptive learning, assessment, and learning analytics, while also describing the evidence as heterogeneous and context-dependent.

For educational use, AI-generated feedback should remain connected to evidence from the student's assessment. Feedback that is unrelated to the diagnosed difficulty may provide little value or may introduce misleading information. Therefore, GRADEMATE AI uses the detected topic-level performance as contextual information for its feedback generation stage.

F. Responsible Use of AI in Education

The application of AI to educational data also introduces concerns involving privacy, transparency, fairness, reliability, and human oversight. UNESCO's guidance on generative AI in education recommends a human-centred approach and emphasizes data privacy, appropriate governance, safety, and meaningful educational use.

Human-centred learning analytics research similarly identifies the need to involve students and teachers in system design and to maintain an appropriate balance between automation and human control.

These considerations are relevant to GRADEMATE AI because student assessment information can represent sensitive educational data. Consequently, the proposed system is positioned as an assistive analytical platform rather than an autonomous authority over student outcomes.

III. RESEARCH GAP

Existing research demonstrates the feasibility of AI-based assessment, learning analytics, personalized learning, automated feedback, and knowledge tracing. However, these capabilities are often studied as separate research areas.

A practical assessment workflow requires several stages to operate together:

Student Response → Evaluation → Topic Mapping → Performance Analysis → Learning-Gap Diagnosis → Personalized Feedback

The research gap addressed by GRADEMATE AI is therefore the integration of these stages into a unified diagnostic workflow.

The proposed system does not attempt to replace established research in automated grading or knowledge tracing. Instead, it provides an application-oriented framework that connects assessment outcomes with topic-level learning information and AI-assisted feedback.

IV PROPOSED METHOD

GRADEMATE AI follows a sequential architecture consisting of assessment processing, response evaluation, topic mapping, performance analysis, learning-gap diagnosis, feedback generation, and visualization.

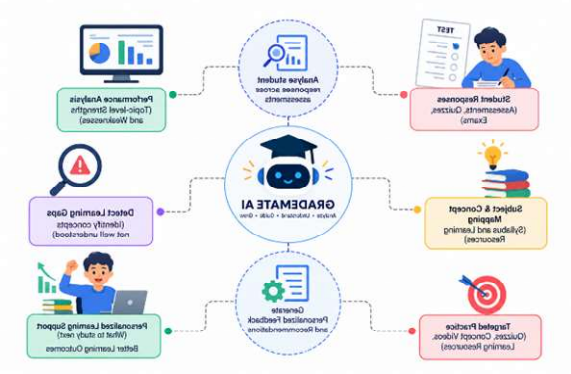

Figure 1: New Culture Fashion Framework

A. Assessment Response Processing

The first stage receives the assessment information submitted by a student. Each assessment item contains the question and the information required for evaluation. Where applicable, the question is also associated with a learning topic or concept.The system preserves the relationship between the question, student response, evaluation result, and learning topic.

This structure is necessary because the later diagnostic stages depend on the ability to associate performance with specific concepts.

B. Response Evaluation

The response evaluation module determines the outcome associated with each submitted answer.

For predefined-response questions, evaluation can be performed through deterministic comparison with the expected answer. For supported natural-language responses, an AI or natural-language-processing component can analyse semantic relevance between the student response and the expected concept.

The output of this stage is a set of question-level evaluation records.

A simplified representation is:

$$R_i = f(Q_i, A_i, E_i)$$

where:

- Q_i= assessment question,
- A_i= student answer,
- E_i= evaluation criteria,
- R_i= resulting evaluation outcome.

The actual evaluation function f depends on the question type and implementation used by GRADEMATE AI.

C. Question-to-Topic Mapping

Each assessment question is associated with a relevant topic or learning concept. This mapping enables the system to move from individual response evaluation to concept-level performance analysis.

For example:

Question	Learning Topic
Q1	Variables
Q2	Conditional Statements
Q3	Loops
Q4	Functions
Q5	Arrays

The mapping can be predefined during assessment creation or generated through an appropriate classification mechanism, depending on the actual implementation.

D. Topic-Level Performance Analysis

After evaluating individual responses, the system aggregates the results according to their associated topics.

Topic performance can be represented as:

$$P_t = \frac{C_t}{N_t} \times 100$$

where:

- P_t= performance for topic t,
- C_t= correct responses associated with topic t,
- N_t= total evaluated questions associated with topic t.

For example, if a learner answers four out of five questions associated with a topic correctly:

$$P_t = \frac{4}{5} \times 100 = 80\%$$

This representation provides a topic-level profile rather than relying exclusively on the overall assessment score.

E. Learning-Gap Diagnosis

The learning-gap module analyses the topic-level performance profile.

A simple threshold-based representation can be expressed as:

$$LG_t = \begin{cases} 1, & P_t < T \\ 0, & P_t \geq T \end{cases}$$

where:

- LG_t= learning-gap indicator,
- P_t= topic performance,
- T= selected diagnostic threshold.

The threshold must be selected according to the actual assessment design and evaluation methodology. It should not be presented as a universal educational standard.

A more robust future implementation could replace a fixed threshold with a model that considers historical performance, question difficulty, number of attempts, and longitudinal mastery.

F. Personalized Feedback Generation

The feedback module uses the diagnostic information to generate learner-specific guidance.

The feedback context can contain:

Student Performance

+

Topic Performance

+

Identified Learning Gap

+

Assessment Context

↓

AI Feedback Generation

↓

Concept Explanation

+

Improvement Guidance

+

Learning Recommendation

The purpose is to transform a diagnostic observation into an understandable explanation.

For example, instead of returning:

Score: 55%

the system can communicate:

Topic requiring attention: Loops
Observed issue: Low performance across loop-related questions
Suggested focus: Loop execution and termination conditions
Next action: Review the concept and attempt a follow-up assessment

The actual wording should be generated from the student's real assessment data rather than from a generic template.

G. Student Performance Visualization

The final layer presents the diagnostic information through a dashboard.

The dashboard can contain:

- Overall assessment score
- Topic-wise performance
- Strong areas
- Areas requiring attention

- Learning-gap indicators
- Personalized feedback
- Recommended learning focus
- Assessment history

Visualization provides a direct way for learners and educators to interpret the results generated by the analytical pipeline.

V. LEARNING-GAP DIAGNOSTIC WORKFLOW

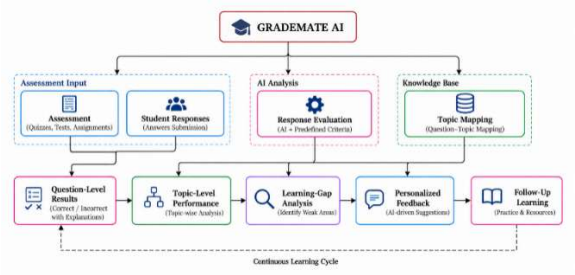

Figure 2: Clustering & Data-Driven Forecasting Framework

Figure 2 represents the transformation of raw assessment responses into learning-oriented information. The workflow begins with response evaluation and proceeds through topic mapping and performance aggregation. The resulting topic profile is analysed to identify areas requiring additional attention. The final diagnostic information is then used to generate personalized feedback and guide subsequent learning activities.

VI. AI-ASSISTED FEEDBACK FRAMEWORK

The AI-Assisted Feedback Framework in GRADEMATE AI is designed to transform assessment results into personalized and actionable learning guidance. Instead of providing only marks or grades, the framework analyses the student's question-level responses and identifies the topics or concepts associated with incorrect or weak responses. These results are then used to generate feedback that explains the identified learning gaps and provides guidance for further learning.

The framework follows a sequential process in which the evaluated assessment responses are first mapped to their corresponding topics. The performance of each topic is then analysed to identify areas in which the student may require additional support. Based on this analysis, the AI feedback component generates personalized feedback according to the student's observed performance. The feedback can include explanations of incorrectly answered concepts, identification of areas requiring improvement, and recommendations for focused learning.

The overall framework can be represented as:

Student Assessment → Assessment Results → Topic-Level Analysis → Learning-Gap Diagnosis → AI Feedback Engine → Personalized Explanation → Learning Recommendation

The framework is intended to support both students and educators. Students receive feedback that is more specific than an overall score, while educators can use the generated insights to understand recurring areas of difficulty. The AI component acts as an assistive layer for interpreting assessment information, while the final educational decision remains with the learner or educator.

Main Components

1. Assessment Result Input:
The framework receives the evaluated responses and question-level results generated from the assessment module.

2. Topic-Level Analysis:
Each question is associated with a particular topic or concept. The framework aggregates the question-level results to determine the student's performance across individual topics.

3. Learning-Gap Diagnosis:
Topics with relatively low performance are identified as potential learning gaps. This allows the system to move

beyond overall marks and focus on specific areas requiring improvement.

4. AI Feedback Generation:
The identified learning gaps are provided to the AI feedback component. The system generates feedback based on the student's performance and the corresponding topic.

5. Personalized Explanation:
Instead of simply indicating that an answer is incorrect, the system can provide a conceptual explanation describing the area that requires further understanding.

6. Learning Recommendation:
The framework can provide targeted learning guidance, such as revising a particular concept, practising related questions, or reviewing supporting learning material.

7. Feedback Presentation:
The generated feedback is presented through the GRADEMATE AI interface so that students can understand their performance and identify the next learning action.

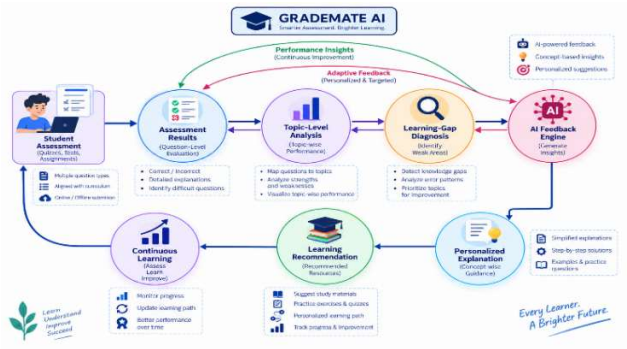

Figure 3: Adaptive Fashion Trend Forecasting and Innovation System

Figure X illustrates the AI-Assisted Feedback Framework used in GRADEMATE AI. The framework processes question-level assessment results, maps responses to relevant topics, identifies potential learning gaps, and generates personalized feedback. By connecting assessment outcomes with topic-level analysis, the system provides students with more meaningful guidance than conventional score-based assessment. The generated feedback focuses on the concepts requiring improvement and can support subsequent learning activities.

VII. SYSTEM IMPLEMENTATION

This section must be customized using your actual technology stack.

Use the following structure, but replace the bracketed portions

A. Front-End Layer

The front-end component provides the user interface through which students interact with assessments and view performance information. The interface includes assessment presentation, response submission, result visualization, and personalized feedback.

Actual technologies: [React / Vite / TypeScript / Tailwind / etc.]

B. Application Layer

The application layer manages assessment requests, response processing, topic mapping, diagnostic operations, and communication between the user interface and analytical services.

Actual technologies: [Node.js / Express / Fast API / etc.]

C. AI Layer

The AI layer performs the functions that require language understanding, semantic evaluation, or personalized feedback generation.

Actual model: [Gemini AI]

Do not write "LLM" here if your system doesn't actually use one.

D. Data Layer

The data layer stores assessment questions, student responses, evaluation results, topic mappings, and performance information.

Actual database: [supa base]

E. Assessment Analytics Layer

The analytics layer aggregates question-level results and calculates topic-level performance. These results are subsequently used by the learning-gap diagnosis component.

VIII. RESULTS AND DISCUSSION

This section is where **your real experimental data must be inserted**.

Do **not** use invented numbers such as 95%, 97%, 98%, etc.

A. Assessment Evaluation Results

Write:

The assessment evaluation component was tested using the selected assessment dataset. Each submitted response was processed and assigned an evaluation outcome according to the implemented assessment rules. The resulting question-level information was subsequently used for topic-level analysis.

Then create:

Table I. Assessment Evaluation Results

Metric	Actual Result
Total Questions	45
Correct Responses	42
Incorrect Responses	3
Overall Performance	93.33%
Assessment Attempts	15

B. Topic-Level Performance

Write:

Topic-level analysis was performed by aggregating question outcomes according to their associated learning concepts. This analysis provides a more detailed representation of performance than the overall assessment score because it identifies how the learner performed across individual topics.

Then:

Table II. Topic-Level Performance

Topic	Questions	Correct	Performance
Programming Fundamentals	12	11	91.67%
Data Structures	10	9	90.00%
Database Management	13	13	100.00%
Software Engineering	10	9	90.00%
Total	45	42	93.33%

C. Learning-Gap Analysis

Write:

The topic-level performance profile was subsequently analysed to identify areas requiring additional attention. Topics falling within the selected diagnostic condition were reported as potential learning gaps. This stage provides an interpretation of assessment outcomes at the concept level and forms the basis for personalized feedback.

Then show a graph:

Figure 4: Topic-Wise Learning-Gap Analysis

A simple bar chart is sufficient.

D. Personalized Feedback Output

Add a screenshot of your actual Grade Mark AI feedback screen.

Caption:

Figure 5: Personalized Feedback Generated by GRADEMATE AI

Then:

Figure 5 demonstrates the feedback generated from the student's assessment profile. The feedback is associated with the identified topic-level performance and provides guidance regarding the concepts requiring additional

attention. This connects the assessment outcome with a subsequent learning activity rather than ending the assessment process at the numerical score.

E. Discussion

The results should be interpreted at both the assessment and diagnostic levels. Overall assessment performance provides a summary of the student's responses, whereas topic-level analysis provides information about the distribution of performance across individual concepts. This distinction is important because learners with similar overall scores may have different areas of difficulty.

The diagnostic workflow implemented in GRADEMATE AI therefore provides an additional analytical layer between assessment evaluation and personalized learning support. The usefulness of this layer depends on the accuracy of response evaluation, the quality of question-to-topic mapping, and the suitability of the diagnostic criteria.

The system should not be interpreted as establishing a definitive measurement of student knowledge from a single assessment. Rather, the identified learning gaps represent areas that may require additional investigation, practice, or assessment. This interpretation is consistent with the broader human-centred perspective in AI-supported learning analytics, where automated outputs should remain interpretable and subject to appropriate human oversight.

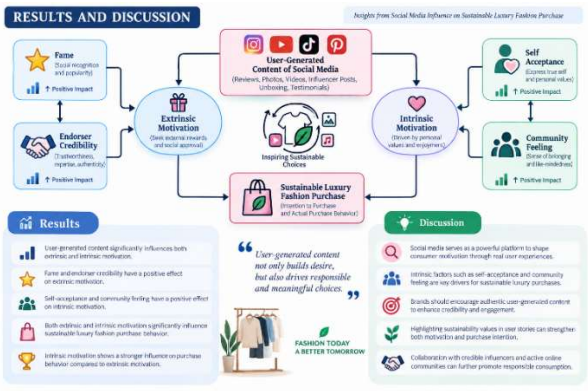

Figure 4: An Explanation of the Conceptual Framework for Research on Sustainable High Fashion

Figure X illustrates the proposed GRADEMATE AI workflow, which transforms student assessment responses into actionable learning insights. The framework progresses from assessment and question-level evaluation to topic-level performance analysis and learning-gap diagnosis, followed by AI-generated feedback, personalized explanations, and targeted learning recommendations. This process establishes a continuous learning cycle in which assessment outcomes are used to guide subsequent learning activities and improve concept-level understanding.

IX. LIMITATIONS

The proposed system has several limitations.

First, the quality of learning-gap diagnosis depends on the assessment design. A topic represented by only a small number of questions may not provide sufficient evidence for reliable diagnosis.

Second, response evaluation becomes more challenging when students provide open-ended answers. Semantic variation, incomplete explanations, and ambiguous responses can affect automated evaluation.

Third, a single assessment provides only a limited observation of a learner's knowledge. A topic identified as a potential learning gap should therefore not automatically be interpreted as a permanent lack of mastery.

Fourth, AI-generated feedback can contain inappropriate or inaccurate explanations if the supplied context is incomplete. Feedback generation should therefore be constrained by assessment evidence and, where appropriate, reviewed by educators.

Finally, student assessment information must be handled responsibly. Privacy, access control, data retention, and appropriate use of AI-generated outputs are important considerations for practical deployment. UNESCO's guidance emphasizes data privacy and human-centred governance when generative AI is used in education and research.

X. FUTURE SCOPE

Several extensions can be investigated in future versions of GRADEMATE AI.

The first is **adaptive assessment**, where subsequent questions are selected based on the learner's demonstrated performance.

The second is **longitudinal knowledge modelling**, in which performance from multiple assessments is combined to estimate changes in concept mastery over time. Knowledge tracing provides an established research direction for this type of modelling.

The system can also be extended with **automated learning-resource recommendation**, allowing identified learning gaps to be connected directly with appropriate study material.

A further extension is **multilingual feedback**, which could make the diagnostic information accessible to learners from different linguistic backgrounds.

For educators, future versions can provide **class-level analytics**, allowing common areas of difficulty to be identified across a group while preserving appropriate student privacy.

Finally, future research should evaluate the system using larger datasets and controlled studies that examine diagnostic reliability, feedback quality, usability, student learning outcomes, and educator acceptance.

XI. CONCLUSION

GRADEMATE AI presents an AI-powered framework for extending conventional educational assessment beyond aggregate marks and grades. The proposed system connects assessment response evaluation with topic-level performance analysis, learning-gap diagnosis, and personalized feedback generation.

The central approach is to associate individual assessment responses with the concepts they are intended to measure. By aggregating question-level results according to these concepts, the system produces a topic-level performance profile that can be used to identify areas requiring additional attention. The diagnostic information is then incorporated into an AI-assisted feedback process designed to provide learner-specific guidance.

The proposed framework does not treat artificial intelligence as a replacement for educators. Instead, it positions AI as an analytical and feedback-support mechanism that can help transform assessment data into more interpretable learning information. The reliability of the resulting diagnosis depends on assessment quality, response evaluation, topic mapping, diagnostic criteria, and appropriate human oversight.

Further experimentation using real student assessment data is required to quantify the diagnostic performance and educational effectiveness of the system. Nevertheless, GRADEMATE AI provides a practical framework for integrating artificial intelligence, learning analytics, and personalized assessment support within a unified educational platform.

REFERENCES

Use actual references rather than the references from your fashion sample. The sample's references are primarily about Vogue and fashion research, so they should not be reused for Grade Mate AI.

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