IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 1, September 2026

Impact Factor: 8.2

AI-Driven Instructional Support System with Dynamic Learning Analytics for Classroom Evaluation

Shaniba Nazneen K[1], Mr. Gireesh. T. K[2], Ameetha Junaina T K[3]

PG Scholar, Department of Computer Science and Engineering[1]

Head, Department of Computer Science and Engineering[2]

Associate Professor, Department of Artificial Intelligence and Data Science[3]

AWH Engineering College, Kuttikkattoor, Calicut, Kerala, India

shanibamtech@gmail.com

Abstract: *The rapid growth of Generative Artificial Intelligence (GenAI) has made AI literacy an essential skill for students, yet conventional classroom and e-learning platforms provide limited support for helping learners understand, question, and critically evaluate AI-generated information. This paper presents an AI-Driven Instructional Support System with Dynamic Learning Analytics for Classroom Evaluation, a role-based, web-based educational platform branded EduMentor that integrates academic and assessment management with a Generative AI instructional-support layer. The system employs Retrieval-Augmented Generation (RAG) and web-scraping-based verification to ground AI responses in course material and trusted external sources, assigns a confidence score to each generated response, and classifies learning content using Bloom's Taxonomy to support progressive cognitive development from Remember and Understand to Apply, Analyze, Evaluate, and Create. A Django backend, a relational database, and a Flutter-based client provide role-specific interfaces for Administrator, HOD, Staff/Teacher, and Student users, along with assessment management, student-performance analysis, and a learning-analytics dashboard. The system was evaluated using 100 functional test cases spanning authentication, assessment management, performance analysis, AI-generated recommendations, and application communication. The platform achieved 94% overall functional accuracy, 100% authentication accuracy, 89% AI-recommendation relevance accuracy, a usability score of 4.4/5 (88%), and an average API response time of 1.8 seconds. The results indicate that an integrated role-based platform combining assessment data with AI-assisted instructional feedback is a feasible and practical approach for data-driven classroom evaluation, provided that AI-generated recommendations continue to be treated as decision-support output requiring teacher verification.*

Keywords: Artificial Intelligence in Education; Learning Analytics; Generative AI; Retrieval-Augmented Generation; Bloom's Taxonomy; Role-Based Access Control; Instructional Support System; Hallucination Detection.

I. INTRODUCTION

Artificial Intelligence (AI) is increasingly incorporated into educational software to support assessment, performance analysis, personalized feedback, and instructional decision-making. AI-driven educational systems can process large volumes of student data and reveal patterns that are not readily visible through conventional mark-based evaluation alone. Learning analytics complements AI-based instructional support by collecting and interpreting data generated during assessment and classroom activity, helping teachers identify performance trends, weak learning areas, and students who require additional support [1]. In practical institutional settings, such platforms must also accommodate multiple stakeholder roles: administrators require system-level management, Heads of Department require aggregated academic information, teachers require assessment and performance functions, and students require access to their own academic records [2].

Conventional academic-management systems primarily store student information, assessments, attendance, and academic records. While useful for administration, they still require teachers to manually interpret assessment results and decide on suitable instructional interventions, since data management, performance analysis, and instructional support typically remain separate. The problem addressed in this work is the absence of an integrated platform that can (i) securely manage role-based academic information, (ii) record and analyze student performance, (iii) provide AI-assisted instructional recommendations, and (iv) present dynamic learning analytics to support classroom evaluation.

A. Objectives

Design and develop a secure, role-based educational platform with customized access for Administrators, HODs, Teachers, and Students.

Record assessment marks and results and analyze student performance to identify weak areas and students needing additional support.

Integrate AI-based instructional support to generate feedback, instructional suggestions, and personalized learning recommendations from available performance information.

Develop learning-analytics functions for monitoring student progress and presenting performance-related indicators.

B. Contributions

An integrated role-based educational platform for Administrator, HOD, Staff/Teacher, and Student stakeholders.

A structured assessment-management component connected to student-performance records.

AI-assisted instructional recommendations, generated using a RAG pipeline and web-scraping-based verification, that are linked to available academic and performance information rather than operating in isolation.

A confidence-scoring and Bloom's-Taxonomy-based classification mechanism that supports response reliability estimation and progressive cognitive-level structuring of learning tasks.

Dynamic learning analytics for identifying trends, weak areas, and progress across users.

A Django backend and Flutter application architecture enabling centralized services with a responsive user interface, evaluated using functional, recommendation-relevance, usability, and API-performance criteria.

This study therefore focuses on the design, implementation, and functional evaluation of EduMentor as an integrated institutional platform. It does not claim to measure long-term learning gains; instead, it evaluates whether role-based academic management, assessment analytics, and AI-assisted instructional recommendations can operate together in a practical classroom-evaluation workflow.

II. RELATED WORK

Artificial intelligence in education spans intelligent tutoring systems, automated assessment, recommendation systems, adaptive learning, and educational data mining, aiming to support personalization and reduce repetitive teacher workload [1], [2]. Intelligent tutoring systems combine learner information, subject knowledge, and instructional strategy to provide targeted support. Recent studies on GenAI-supported learning highlight both the opportunities of conversational assistance and the safeguards required for classroom use [3], [4]. AI literacy, prompt engineering, and critical thinking have been identified as interconnected competencies necessary for effective classroom use of GenAI [1], while systematic reviews of GenAI literacy and AI-assisted education identify pedagogical enhancement, writing assistance, ethics, risk, and the need for empirical system-level evaluation as recurring themes [12], [18].

Studies in science education emphasize the role of language, discourse, and natural-language interaction in GenAI-supported learning [9], motivating the conversational design adopted in this work. Role-based educational platforms

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, September 2026
Impact Factor: 8.2

combining personalized learning with scalable access control have also been proposed, underscoring the value of differentiated access for administrators, academic managers, teachers, and students [10]. Prompt engineering itself has been reviewed as a distinct AI-literacy competency, with scoping reviews identifying guided learning, learning outcomes, and GenAI risk as recurring themes, and highlighting persistent gaps in structured prompt-engineering education [6], [20].

A. Research Gap

The reviewed literature points to a practical gap: many systems emphasize academic-record management, AI tutoring, or learning analytics separately, whereas institutions benefit from integrating these functions into a single role-based platform. Specific limitations include fragmented support for AI literacy, prompt engineering, and ethical AI use; limited adaptation of explanations to individual learner ability; insufficient support for critical thinking through hints and guiding questions; limited hallucination awareness and response verification; insufficient teacher control over prompts, AI-use boundaries, and monitoring; and limited longitudinal evidence on whether sustained GenAI interaction improves AI literacy over time. Table I summarizes how the proposed system responds to these limitations.

Research Area	Existing Limitation	System Response
Academic record management	Often focused on storage and reporting	Integrated assessment and student-performance management
AI instructional support	May operate separately from institutional records	AI recommendations linked to available performance information
Learning analytics	Analytics isolated from operational workflows	Analytics integrated with assessment and performance modules
Multi-role access	Different user groups require different permissions	Administrator, HOD, Staff/Teacher, and Student role-based access
Decision support	Teachers must interpret raw scores manually	AI-assisted instructional suggestions and performance summaries
Application integration	Multiple tools create fragmented workflows	Unified Django backend and Flutter interface

Table I. *Research gap and corresponding system response.*

III. PROPOSED SYSTEM DESIGN AND METHODOLOGY

The project follows a software-engineering methodology comprising requirement identification, system design, database design, module implementation, integration, and experimental evaluation.

A. System Architecture

The implemented architecture consists of four layers: (i) a Flutter presentation layer providing role-specific interfaces; (ii) a Django application/API layer managing authentication, business logic, assessment processing, student records, analytics, and API services; (iii) a relational database layer storing institutional, course, assessment, and interaction data; and (iv) an AI/analytics services layer that generates grounded instructional recommendations and learning-analytics outputs from available performance and learning-context information.

B. System Workflow

User access: Students and teachers access the platform through role-specific interfaces.

Authentication and role management: Users are authenticated and assigned Administrator, HOD, Teacher, or Student permissions.

Lesson and content management: Teachers create/upload lessons, materials, and activities; students access assigned content.

Teacher prompt dashboard: Teachers define lesson-specific prompts and learning objectives for the Generative AI assistant.

AI prompt-engineering module: Student prompts are refined according to learning context, supporting prompt-writing skill development.
Generative AI engine: An LLM processes the student query together with lesson context and prompt to generate a personalized response.
Hallucination detection and confidence scoring: Generated responses are analyzed for reliability and assigned a confidence score.
Adaptive feedback generator: The system returns hints, guiding questions, and explanations calibrated to the learner's level rather than direct answers.
AI literacy assessment: Student AI awareness, prompt-writing ability, critical evaluation, and ethical AI usage are assessed periodically.
Response validation layer: AI responses are checked against course materials and trusted sources before being presented.
Learning analytics dashboard: Interactions, engagement, prompt quality, and progress are analyzed and visualized.
Database: User profiles, lessons, prompts, AI interactions, assessments, and performance records are securely stored.
Teacher performance reports: Teachers receive reports on student progress, literacy improvement, and areas requiring intervention.

C. Major Modules

The platform comprises Authentication and Authorization, Administrator, HOD, Staff/Teacher, and Student modules, an Assessment Management module for creating and scoring assessments, a Student Performance Analysis module for trend and weak-area identification, an AI-Based Instructional Support module for feedback and recommendation generation, and a Learning Analytics module for visualizing engagement and progress indicators.

D. Database Design

The implemented database is organized around the academic-management workflow shown in Table II.

Entity/Table	Purpose
Department	Stores departmental information
Staff	Stores staff/teacher information
Student	Stores student information
Student Subject	Associates students with academic subjects
Attendance	Stores attendance-related records
Assignment	Stores assignment information and related records
Notes	Stores academic notes/material references
Feedback	Stores feedback-related information
Assessment/Performance	Supports marks and performance analysis

Table II. *Implemented database entities.*

E. Security Considerations

Authentication is required before protected functions are accessed, and role-based authorization restricts functionality according to institutional responsibility. All database operations pass through the application backend, and credentials are stored using secure password hashing rather than embedding secrets in client-side code. The proposed security workflow can be summarized as: User → Secure Authentication → Role-Based Authorization → Input Validation → Prompt Security → Generative AI Engine → Hallucination and Safety Detection → Response Validation → Secure Response → Encrypted Database → Audit and Monitoring, targeting Confidentiality, Integrity, Availability, Privacy, Accountability, and Responsible AI usage.

IV. IMPLEMENTATION

The system was implemented as an educational management and instructional-support platform, branded EduMentor, using a Django backend, a relational (MySQL) database, and a Flutter-based client, as summarized in Table III.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, September 2026
Impact Factor: 8.2

Component	Technology
Backend	Python and Django
Application interface	Flutter
Database	Relational database / MySQL
API communication	Django-based backend services
AI layer	AI-based instructional recommendation service
Development tools	PyCharm / VS Code

Table III. *Development environment.*

A. Knowledge Extraction and Question Generation Pipeline

An intelligent knowledge-extraction pipeline processes uploaded educational PDF documents. Text, tables, and images are extracted using PyMuPDF, with Tesseract OCR applied to scanned or image-based pages. Extracted text is cleaned using NLTK and regular-expression-based preprocessing, including segmentation, tokenization, stop-word removal, and lemmatization, and then divided into semantically coherent chunks using recursive character, semantic, and sliding-window chunking strategies. Each chunk is converted into a dense vector embedding using Sentence-BERT (SBERT) and indexed in a vector database such as FAISS or ChromaDB for approximate-nearest-neighbor similarity search. A Retrieval-Augmented Generation (RAG) stage retrieves the most relevant chunks using Top-K retrieval, cosine similarity, and Maximum Marginal Relevance (MMR), after which a large language model generates context-aware multiple-choice, short-answer, descriptive, and true/false question–answer pairs. Generated questions are classified by cognitive level using Bloom's Taxonomy and by difficulty level using machine-learning classifiers.

B. Conversational Chatbot, Verification, and Confidence Scoring

Student questions are processed through user-intent detection and query enhancement, including query expansion, rewriting, HyDE, and multi-query retrieval, before RAG-based dense retrieval and cross-encoder re-ranking identify supporting document chunks. Llama-3/Gemma-based generation produces a grounded response constrained to the retrieved context. A web-scraping module retrieves supplementary information from trusted educational and government sources where external verification is required. The generated answer is then compared with the retrieved and external evidence using semantic-similarity, overlap-based, and inference-based checks to determine whether it is supported, contradicted, or unrelated to the available evidence, and a High, Medium, or Low confidence label is assigned accordingly. The final response is presented together with PDF citations, web references, the assigned confidence score, the Bloom's-Taxonomy level, and the predicted difficulty level, giving students a transparent, evidence-supported output rather than an unqualified answer.

C. Role-Based Interfaces

Separate interfaces are provided for each institutional role. The Student interface offers login/profile, lessons and resources, the AI learning assistant, prompt-engineering practice, AI-literacy assessment, feedback/hints, and a progress dashboard. The Teacher interface offers course/lesson management, the prompt-engineering dashboard, interaction monitoring, AI-literacy-assessment management, learning analytics, and performance reports. The Administrator interface offers user/role management, system configuration, access control, security monitoring, and audit logs. Authentication follows the sequence Login → Credential Verification → Role Identification → Authorization → Role-Specific Dashboard.

D. Backend–Application Communication

The Flutter client communicates with the Django backend to authenticate users, retrieve and submit academic information, process assessment-related requests, and obtain analytics or AI-assisted results. Under the evaluated conditions, the average measured API response time was 1.8 seconds.

V. RESULTS AND DISCUSSION

The evaluation used 100 functional test cases covering authentication, assessment management, student-performance analysis, learning analytics, AI-generated recommendations, and application communication, as summarized in Table

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 1, September 2026 Impact Factor: 8.2

IV. The available evidence does not include a controlled participant-level pre-test/post-test study; hence, no statistically significant claim of learning or AI-literacy improvement is made.

Evaluation Category	Functions Evaluated
Authentication and authorization	Registration/login, password validation, role-based access
Assessment management	Creation/update, submission/mark entry, result calculation, history
Student performance analysis	Score analysis, trend identification, comparison, support identification
AI instructional support	Feedback, learning-difficulty identification, instructional suggestions
Learning analytics	Progress monitoring, weak-area identification, visualization, reports
Application performance	API response, database operations, communication, usability

Table IV. *Evaluation categories.*

A. AI-Generated Recommendation Evaluation

Of the 100 AI-generated recommendations evaluated, 89 were judged relevant, 7 partially relevant, and 4 irrelevant, giving an observed relevance rate of 89% for fully relevant recommendations, as shown in Table V.

Evaluation Parameter	Number	Percentage
Total AI-generated recommendations	100	100%
Relevant recommendations	89	89%
Partially relevant recommendations	7	7%
Irrelevant recommendations	4	4%
Observed recommendation accuracy	89	89%

Table V. *AI-generated recommendation evaluation.*

B. Overall System Performance

Table VI presents the consolidated system results across functional accuracy, AI recommendation accuracy, usability, and API response time.

Metric	Result	Interpretation
Functional accuracy	94%	Majority of evaluated functions operated successfully
AI recommendation accuracy	89%	89 of 100 recommendations judged relevant
Usability	4.4/5 (88%)	Positive evaluation of interface and interaction
Average API response time	1.8 s	Observed average under evaluated conditions

Table VI. *Consolidated system results.*

C. Discussion

The evaluation indicates that the platform can integrate role-based access, assessment management, performance analysis, AI-assisted instructional support, and learning analytics in a single operational workflow. The 94% functional accuracy suggests that most tested functions operated as expected, and authentication achieved 100% accuracy across the evaluated scenarios, demonstrating reliable access control within the test environment. The 89% fully relevant AI-recommendation rate indicates that AI-generated instructional support is broadly useful, but the presence of partially relevant and irrelevant outputs confirms that teacher verification remains necessary. The learning-analytics functions show that the platform can transform assessment data into performance indicators that help teachers identify weak areas and progress patterns. The 4.4/5 (88%) usability score indicates a positive evaluation of the interface and navigation, and the 1.8-second average API response time indicates acceptable communication performance under the evaluated conditions, together supporting the feasibility of the platform as a classroom-evaluation and instructional-support tool.

D. Limitations

The reported results are based on functional and recommendation-relevance evaluation rather than a controlled longitudinal educational study.

The evaluation does not provide sufficient evidence for statistical claims about improvement in student learning or AI literacy.
The AI-recommendation evaluation is based on relevance judgments and does not constitute a complete factuality or hallucination benchmark.
Response-time measurements reflect the reported experimental conditions and may vary in production deployments.
Generalizability to other institutions, subjects, and larger user populations requires further validation.

VI. CONCLUSION AND FUTURE SCOPE

This paper presented the design, implementation, and evaluation of an AI-Driven Instructional Support System with Dynamic Learning Analytics for Classroom Evaluation. The system combines role-based authentication, academic and assessment management, student-performance analysis, RAG-based AI-assisted instructional recommendations with confidence scoring and Bloom's-Taxonomy classification, learning analytics, and backend–application communication within a single Django/Flutter platform. The reported evaluation achieved 94% functional accuracy, 89% fully relevant AI recommendations, a usability score of 4.4/5 (88%), and an average API response time of 1.8 seconds, indicating that the platform provides a practical foundation for data-driven classroom evaluation and AI-assisted instructional decision support. These findings also confirm that AI-generated recommendations should be treated as teacher-verified decision-support outputs rather than autonomous instructional decisions.
Future work will focus on integrating a dedicated conversational Generative AI tutor with lesson-aware retrieval and controlled instructional prompting, adding explainable recommendation generation so that teachers can inspect the evidence underlying AI suggestions, developing adaptive learner modelling and personalized intervention strategies, and conducting a controlled pre-test/post-test study with an adequate participant sample and statistical significance testing. Further work will also evaluate the system across multiple institutions, subjects, and larger user populations, strengthen privacy, audit logging, and deployment security, and extend the platform toward multilingual and accessibility-oriented interfaces in support of India's Viksit Bharat 2047 vision [23].

REFERENCES

[1] Y. Walter, "Embracing the future of artificial intelligence in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education," Int. J. Educ. Technol. High. Educ., vol. 21, Art. no. 15, 2024.
[2] B. Batsaikhan and A.-P. Correia, "The effects of Generative Artificial Intelligence on intelligent tutoring systems in higher education: A systematic review," Stud. Technol. Enhanc. Learn., vol. 4, no. 1, 2024.
[3] Y. Tu, J. Chen, and C. Huang, "Empowering personalized learning with generative artificial intelligence: Mechanisms, challenges and pathways," Front. Digit. Educ., vol. 2, Art. no. 19, 2025.
[4] A. Létourneau, M. Deslandes Martineau, P. Charland, J. A. Karran, J. Boasen, and P. M. Léger, "A systematic review of AI-driven intelligent tutoring systems (ITS) in K-12 education," npj Sci. Learn., vol. 10, Art. no. 29, 2025.
[5] H. Farhood, M. Nyden, A. Beheshti, and S. Muller, "Artificial intelligence-based personalised learning in education: A systematic literature review," Discov. Artif. Intell., vol. 5, Art. no. 331, 2025.
[6] D. Lee and E. Palmer, "Prompt engineering in higher education: A systematic review to help inform curricula," Int. J. Educ. Technol. High. Educ., vol. 22, Art. no. 7, 2025.
[7] S. Bećirović, E. Polz, and I. Tinkel, "Exploring students' AI literacy and its effects on their AI output quality, self-efficacy, and academic performance," Smart Learn. Environ., vol. 12, Art. no. 29, 2025.
[8] R. Salhab and M. M. Aboushi, "Influence of AI literacy and 21st-century skills on the acceptance of generative artificial intelligence among college students," Front. Educ., vol. 10, Art. no. 1640212, 2025.
[9] C. Hou, G. Zhu, V. Sudarshan, F. S. Lim, and Y. S. Ong, "Measuring undergraduate students' reliance on generative AI during problem-solving: Scale development and validation," Comput. Educ., vol. 234, Art. no. 105329, 2025.

[10] L. Yan, R. Martinez-Maldonado, Y. Jin, V. Echeverria, M. Milesi, J. Fan, L. Zhao, R. Alfredo, X. Li, and D. Gašević, "The effects of generative AI agents and scaffolding on enhancing students' comprehension of visual learning analytics," Comput. Educ., vol. 234, Art. no. 105322, 2025.

[11] A. Mimoudi, "Generative AI to bridge the educational divide: Personalized learning and challenges," Soc. Sci. Humanit. Open, vol. 12, Art. no. 102140, 2025.

[12] J. Park, "A systematic literature review of generative artificial intelligence (GenAI) literacy in schools," Comput. Educ. Artif. Intell., vol. 9, Art. no. 100487, 2025.

[13] N. Mukaida, K. Tsutsumi, Y. Amakawa, S. Ahama, M. Nakata, and R. Takaoka, "Teaching practice and evaluation using a generative AI-based instructional support tool," in Proc. 25th IEEE Int. Conf. Adv. Learn. Technol. (ICALT), 2025.

[14] W. Yan, T. Nakajima, and R. Sawada, "Beyond tool use: Tracking the evolution of generative AI literacy among university students through a process-oriented investigation," Comput. Educ. Artif. Intell., vol. 9, Art. no. 100465, 2025.

[15] J. Kong, J. Liu, G. Chen, et al., "Assessing AI literacy in college students: The mediating role of self-efficacy in motivational commitment pathways," Educ. Inf. Technol., vol. 30, pp. 23957–23979, 2025.

[16] S. Elnaffar, F. Rashidi, and A. Z. Abualkishik, "Teaching with AI: A systematic review of chatbots, generative tools, and tutoring systems in programming education," Int. J. Learn. Teach. Educ. Res., vol. 25, no. 1, pp. 1–28, 2026.

[17] K. Qian, S. Liu, T. Li, et al., "Towards reliable generative AI-driven scaffolding: Reducing hallucinations and enhancing quality in self-regulated learning support," Comput. Educ., vol. 240, Art. no. 105448, 2026.

[18] S. Feng and A. Carolus, "Artificial intelligence literacy at school: A systematic review with a focus on psychological foundations," Comput. Educ. Artif. Intell., vol. 10, Art. no. 100551, 2026.

[19] C. Li, H. Cui, and L. S. Hagedorn, "The cognitive impact of ChatGPT in higher education: A systematic review of critical and creative thinking outcomes," Comput. Educ. Artif. Intell., vol. 10, Art. no. 100571, 2026.

[20] F. N. N. Pangestu, I. Hamidah, L. Widaningsih, A. G. Abdullah, and N. A. Saputra, "A scoping literature review of prompt engineering for bridging students' AI literacy in higher education," Comput. Educ. Artif. Intell., vol. 10, Art. no. 100581, 2026.

[21] M. Yilmaz, A. Gauthier, and M. Cukurova, "Supporting online learners' regulation skills with the help of learning analytics and generative artificial intelligence," Educ. Technol. Res. Dev., vol. 74, pp. 1223–1252, 2026.

[22] T. Nazaretsky, H. Gabbay, and T. Käser, "Can students judge like experts? A large-scale study on the pedagogical quality of AI and human personalized formative feedback," Comput. Educ. Artif. Intell., vol. 10, Art. no. 100533, 2026.

[23] M. Rehman, M. A. Dar, and I. Rasool, "AI literacy at higher education and India's vision Viksit Bharat 2047: A systematic review," Discov. Artif. Intell., vol. 5, Art. no. 294, 2025.

[24] S. Caspari-Sadeghi, "AI literacy for teacher educators: A holistic curriculum for capacity-building in higher education," Front. Educ., vol. 11, Art. no. 1745768, 2026.

[25] S. Ba, X. Shi, S. Wu, and G. Lu, "Artificial intelligence agents in computer-supported collaborative learning: A systematic literature review," Comput. Educ. Artif. Intell., vol. 10, Art. no. 100579, 2026