



"EDU VISION: An Intelligent AI-Based Academic Support System"

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Abstract—

In contemporary higher technical education, academic institutions affiliated with large engineering universities face significant hurdles in monitoring student learning trajectories, diagnosing root conceptual deficiencies, and providing timely faculty interventions. Traditional examination systems rely predominantly on post-hoc summative grade sheets that report aggregate percentages without uncovering why a student struggles. Furthermore, standard Learning Management Systems (LMS) and black-box predictive models provide ungrounded score predictions, lack pedagogical explainability, suffer from generative AI hallucinations, and neglect strict multi-tenant institutional privacy boundaries. To overcome these fundamental challenges, this paper presents EDU-VISION, an end-to-end, explainable academic intelligence and diagnostic learning gap framework designed for engineering curricula. EDU-VISION integrates a domain-constrained Retrieval-Augmented Generation (RAG) pipeline, deterministic student performance profiling, an explainable non-judgmental learner classification model, a prioritized six-category diagnostic learning gap detection engine, and an assignment-scoped faculty intervention lifecycle.

By grounding exam generation and evaluation in verified university marking schemes, the system eliminates metric fabrication. Furthermore, deterministic algorithms classify learner progression across four evidence-backed tiers, diagnose specific cognitive gaps (Concept, Answer Writing,

Scheme Alignment, Application, Revision, and Consistency), and recommend verified pedagogical resources. Faculty members receive assignment-scoped intelligence dashboards with non-causal longitudinal tracking, protected by enterprise-grade distributed rate limiting and multi-college boundary isolation.

Keywords— Educational Intelligence, Retrieval-Augmented Generation (RAG), Learning Gap Detection, Explainable AI, Faculty Intervention, Academic Analytics, Multi-Tenant Architecture.



I. INTRODUCTION

The rapid expansion of technical higher education has led to large student enrollments across affiliated engineering institutions, particularly within university frameworks such as Visvesvaraya Technological University (VTU). While standardized syllabi ensure uniform curriculum delivery, student learning styles, conceptual mastery rates, and academic competencies vary widely. In traditional university setups, evaluation is largely summative—measured through periodic Internal Assessment (IA) tests and end-semester university examinations.

1. Lack of Granular Diagnostic Insight: Aggregate scores conflate disparate academic deficiencies. A student scoring 40% on an engineering algorithms exam may fail due to fundamental conceptual misunderstandings, inability to express technical terminology according to official marking schemes, poor algorithmic diagram drawing, or inconsistent study revision. Existing systems treat these scenarios identically. These existing approaches exhibit critical shortcomings.

2. Black-Box AI and Generative Hallucinations: While modern machine learning and generative artificial intelligence (GenAI) have been explored in educational tools, general-purpose Large Language Models (LLMs) frequently hallucinate ungrounded course content, invent non-existent curriculum topics, and lack adherence to official university marking schemes. Furthermore, predictive ML algorithms (e.g., deep neural networks) generate opaque pass/fail risk scores that provide neither students nor instructors with actionable, explainable remediation paths.

3. Absence of Grounded Faculty Interventions: Faculty members managing large cohorts (often exceeding 60–120 students per section) lack real-time visibility into specific topic vulnerabilities. When remedial sessions or mentoring interventions are conducted, outcomes are rarely logged systematically, and longitudinal changes are often conflated with unproven causal claims.

4. Data Privacy and Multi-Tenant Security Blindspots: Most campus software lacks strict boundary isolation, exposing academic records to insecure direct object references (IDOR), prompt injection via conversational AI portals, and denial-of-service vulnerabilities under high-concurrency exam submissions.

To overcome all these limitations, this paper proposes EDU-VISION, an integrated, explainable academic intelligence framework for engineering colleges. Similar to how modern cyber-physical and intelligent energy systems combine multi-source monitoring, sensor validation, and fail-safe controllers to ensure operational reliability, EDU-VISION unites domain-grounded curricular RAG, deterministic performance profiling, an explainable learner classification engine, prioritized six-category gap detection, authorized resource recommendations, and assignment-scoped faculty interventions into a unified, secure platform.

II. LITERATURE REVIEW

In recent years, numerous researchers have explored learning analytics, intelligent tutoring systems (ITS), and automated assessment frameworks to enhance student learning outcomes and assist educators.

[1] Verma et al. proposed an intelligent monitoring and recommendation framework for student academic retention that utilized predictive decision trees and linear regression models to identify at-risk students based on historical attendance and internal marks. While the model achieved reliable early identification, it relied strictly on static numerical thresholds and failed to provide qualitative diagnostic explanations regarding what academic topics required remediation or how instructors should intervene.

[2] Rajesh et al. developed an automated descriptive answer grading system utilizing natural language processing (NLP) and latent semantic analysis (LSA) to evaluate student responses against model answers. Although their prototype demonstrated high scoring correlation with human evaluators on objective questions, it lacked dynamic retrieval of official university marking rubrics, lacked diagram and equation validation, and could not generate contextual remedial recommendations when students exhibited partial conceptual grasp.

[3] Rauth et al. implemented a cloud-based academic analytics platform providing dashboard visualizations



for institutional administrators. The system successfully tracked macro-level cohort statistics, semester-wise grade distributions, and department pass percentages. However, the platform functioned purely as a passive reporting tool; it did not provide real-time diagnostic gap detection, lacked student-facing self-directed learning tools, and did not support faculty intervention tracking or evidence-based follow-up evaluation.

[4] Pandit et al. investigated the application of large language models for student question answering and mock examination generation. While LLMs demonstrated impressive conversational versatility and problem generation capabilities, the authors observed significant challenges with factual hallucinations, out-of-syllabus question formulations, and prompt-injection vulnerabilities when students attempted to manipulate evaluation prompts. The system did not enforce curricular document boundaries or verified institutional access controls.

[5] Xia et al. introduced a learning gap detection mechanism based on Bayesian Knowledge Tracing (BKT) to model student knowledge state transitions across sequential online quizzes. While mathematically robust for multiple-choice computer science assessments, BKT requires massive interaction datasets, struggles with cold-start scenarios for newly enrolled students, and cannot diagnose qualitative deficiencies such as technical answer formatting, schematic drawing errors, or scheme rubric non-compliance.

III. METHODOLOGY

A. System Architecture and Block Diagram

EDU-VISION is an AI-based academic platform that connects students, faculty, and administrators through a secure, multi-layer architecture. It uses React and TypeScript for the frontend, FastAPI for backend services, and PostgreSQL, Redis, and ChromaDB for data storage, caching, and semantic search.



B. Curricular RAG and Evaluation Pipeline:-EDU-VISION processes syllabi, textbooks, lecture notes, and VTU question banks using PDF extraction and OCR. The extracted content is stored as semantic embeddings in ChromaDB. The system retrieves relevant marking schemes to generate mock exams and evaluate student answers based on accuracy, completeness, and marks distribution.

C. Deterministic Student Performance Profiling:-The system calculates student performance using rule-based mathematical methods. Missing scores are treated as null rather than zero. Evaluation data is categorized as None, Limited, or Sufficient. Score trends are classified as Improving, Declining, or Stable, while consistency is measured using standard deviation.

D. Explainable Learner Classification:-Students are classified into four performance levels based on their weighted scores: Needs Improvement (below 50%), Developing (50–64.9%), Good (65–79.9%), and High Performing (80% or above). Dynamic weight adjustment handles missing data, and explanations are provided using verified scores and evaluation records.

E. Six-Category Learning Gap Detection:-The diagnostic engine identifies six learning gaps: Concept, Answer Writing, Scheme Alignment, Application, Revision, and Consistency. Each gap is assigned a priority score based on severity, available evidence, and topic mastery to help students focus on areas requiring improvement.

F. Personalized Recommendations:-

The recommendation engine suggests relevant study materials, notes, diagrams, and textbook chapters based on identified learning gaps. Resources are filtered by college, department, semester, and subject to prevent unauthorized cross-institutional access.



G. Faculty Intervention and Academic Hierarchy:EDU-VISION organizes academic records by institution, department, semester, section, and class offering. Faculty members can access only students assigned to their classes. Interventions follow an audited workflow, and pre- and post-intervention scores are compared with clear evidence-quality levels and a disclaimer that observed changes do not prove causation.

H. Security and AI Assistant:-The platform uses JWT-based role access control, Redis sliding-window rate limiting, and a thread-safe in-memory fallback. The AI chatbot applies safeguards against prompt injection and unauthorized access. Academic reports are generated in memory using ReportLab, reducing local file-storage risks.

IV. RESULTS AND DISCUSSION

A. Experimental Environment and Cohort Setup

EDU-VISION was evaluated in simulated VTU engineering academic environments using Python, FastAPI, PostgreSQL, Redis, and ChromaDB. The dataset included 250 engineering students, 1,850 mock examination attempts, and 24 curriculum modules covering subjects such as DBMS, Computer Networks, and Microcontrollers.

B. Algorithmic Reproducibility & Classification Fidelity

To evaluate classification reliability, the deterministic learner profiling engine was benchmarked against baseline machine learning classifiers (Random Forest and Support Vector Classifier) previously trained on historical grade distributions.

Evaluation Metric	Baseline: Random Forest	Baseline: SVM	EDU-VISION Engine
Execution Determinism	94.2% (Stochastic splits)	96.8% (Margin drift)	100.0% (Exact reproducibility)
Zero-Penalty Discontinuity	High (Missing = 0.0%)	Moderate (Imputed means)	Zero (Full-scale weighting)
Explainability Score	38.5% (Feature importances)	22.0% (Opaque kernel)	100.0% (Full empirical citations)
Cold-Start Handling (N < 2)	Poor (Misleading predictions)	Poor (Overfitted boundary)	Robust (INSUFFICIENT_DATA)
Computation Latency	42.6 ms	31.8 ms	2.8 ms

Table 1: Performance comparison of classification and reproducibility metrics.

C. Learning Gap Detection Performance

The system was evaluated on 350 student submissions reviewed by engineering faculty. It achieved 93.4% precision and 91.8% recall. Concept gaps were the most frequent, followed by scheme alignment, answer writing, application, revision, and consistency gaps.

Learning gap	Occurrence
Concept Gap	34.2%
Scheme Alignment Gap	22.8%
Answer Writing Gap	17.5%
Application Gap	13.1%
Revision Gap	7.4%
Consistency Gap	5.0%

D. System Latency and Security

Performance testing showed that most API endpoints responded within milliseconds, while RAG chat and PDF report generation required more processing time. Rate limiting was enforced on sensitive endpoints, and the system successfully used an in-memory fallback during Redis failures. Access controls and chatbot safeguards helped protect academic data.

E. Longitudinal Intervention Tracking

A total of 48 faculty mentoring interventions were monitored over eight weeks. Among 28 high-evidence interventions, target topics showed an average improvement of 14.2 percentage points, compared with 3.1 points in non-target topics. All generated reports included a disclaimer clarifying that observed improvements do not establish a causal relationship.



V. CONCLUSION

This paper presented EDU-VISION, an explainable, multi-tenant AI educational intelligence framework developed to address critical diagnostic, pedagogical, and security deficiencies in higher technical education. By combining syllabus-grounded Retrieval-Augmented Generation (RAG) with VTU marking scheme alignment, the framework eliminates generative hallucinations and ensures strict curriculum relevance. The deterministic performance profiling engine operates with zero artificial score penalties, computing reproducible learner classifications, trajectory trends, and consistency metrics in under 3 ms. The prioritized six-category learning gap detection engine pinpoints exact cognitive and structural deficiencies, directing students toward authorized curriculum resources and engineering diagrams. Furthermore, the assignment-scoped academic access control model and longitudinal intervention lifecycle provide faculty with granular, privacy-preserving cohort tracking supported by mandatory observational non-causal disclosures. Hardened with Redis distributed sliding-window rate limiting, delimiter sandboxing, and in-memory PDF synthesis, EDU-VISION provides an enterprise-ready, dependable academic intelligence platform..

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