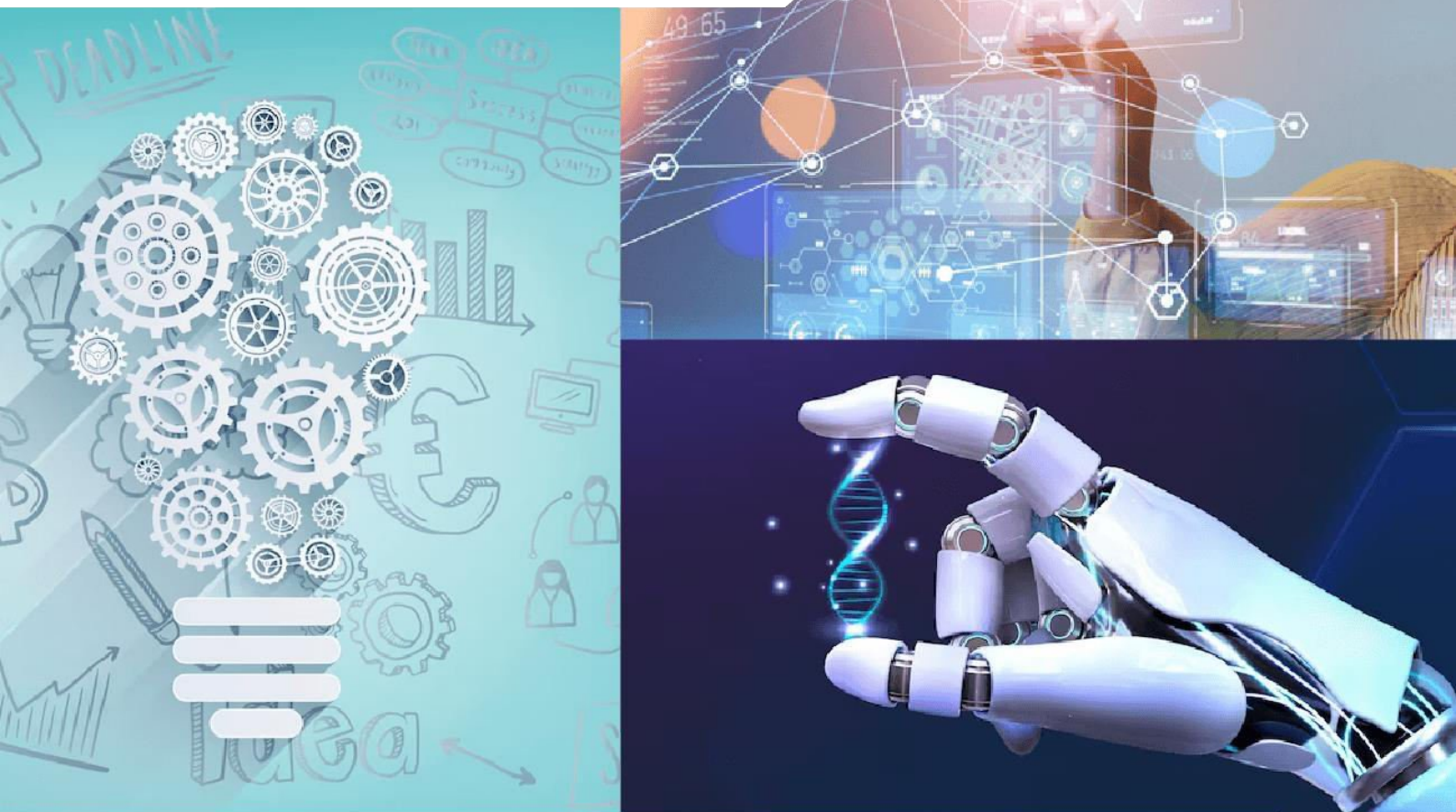




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AI-Powered Learning Management System with Intelligent Tutoring and Real-Time Analytics

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ABSTRACT: Online education has grown sharply in recent years, placing pressure on institutions to adopt platforms that do more than store and deliver course files. Conventional Learning Management Systems satisfy administrative needs but fall short in personalised academic support, real-time performance intelligence, and contextually aware doubt resolution. This paper presents the design and development of an AI-Powered Learning Management System (AI-LMS) built on Python/Flask and SQLite, integrating an LLM-based AI tutor via the Groq API, a Retrieval-Augmented Generation pipeline for PDF-based question answering, automated quiz evaluation, multilingual interaction, and a visual analytics dashboard. The system was evaluated through functional, security, performance, and boundary testing. Results confirm quiz evaluation within one second, AI tutor responses within one to two seconds, and stable operation under 25 concurrent users.

KEYWORDS: Learning Management System, Artificial Intelligence, Retrieval-Augmented Generation, Intelligent Tutoring System, Learning Analytics, Flask, Large Language Model, Adaptive Learning

I. INTRODUCTION

Over the past two decades, information and communication technologies have fundamentally altered how education is delivered and consumed. Physical classrooms are increasingly supplemented or replaced by digital platforms that remove geographical and temporal constraints, giving learners the flexibility to engage with curriculum materials outside fixed schedules. In this context, Learning Management Systems have become core infrastructure for academic institutions at every level.

Despite widespread adoption, mainstream LMS platforms treat all learners uniformly. Kaiwinit et al. [1] documented significant shortcomings in existing LMS platforms, particularly their inability to support diverse learning ecosystems. Students exhibit distinct learning styles that fixed delivery mechanisms cannot accommodate [2], and assessment feedback is typically reduced to a final score with no actionable guidance.

Research confirms that frequent online quizzes paired with immediate automated feedback create significantly more effective learning environments [7]. Students in AI-driven personalised systems achieved a mean score gain of 16.2 points compared to 7.1 points for control groups following conventional instruction [14]. LLM-powered intelligent tutoring systems can construct learner profiles and generate adaptive learning paths [3], while RAG addresses the hallucination problem of plain LLMs by grounding responses in institution-specific documents [13].

This paper describes the design and implementation of an AI-LMS addressing these gaps. Contributions include: (1) a modular role-based web platform unifying content management, assessment, AI tutoring, and analytics; (2) a RAG-based PDF chat module; (3) a multilingual AI interaction layer; and (4) an empirical evaluation with quantified benchmarks.

II. LITERATURE SURVEY

A. Traditional Learning Management Systems

Kaiwinit et al. [1] proposed the Ruamrean platform to address shortcomings in existing LMS deployments across five provinces with 1,030 participants, confirming that modern education demands platforms beyond simple content repositories. Graf et al. [2] proposed an automatic approach for identifying student learning styles within LMS environments using the Felder-Silverman model evaluated across 127 students, demonstrating that LMS platforms should adapt to individual learning styles.

B. Intelligent Tutoring Systems

Huang et al. [3] presented an LLM-powered ITS for AI education that constructs learner profiles, diagnoses knowledge gaps, and generates adaptive learning paths through knowledge graph reasoning and RAG-based content synthesis. El Khayat et al. [4] applied data mining techniques to 790 students to uncover hidden learning patterns supporting AI-powered tutoring. Suhail and Rajakumari [5] proposed a personalised and explainable AI tutor framework using LLMs with SHAP-based explainability, exceeding baseline ITS by 28.7% in accuracy with a satisfaction score of 4.8 out of 5.

C. Online Assessment and Automated Evaluation

Gordillo et al. [6] presented an online authoring tool for creating reusable quizzes with an Audience Response System for instant classroom feedback, achieving excellent acceptance from teachers and students. Pishchukhina and Allen [7] investigated frequent online formative assessment with immediate automated feedback in a large postgraduate cohort, finding a strong correlation between quiz attempt frequency and end-of-term exam scores.

D. Retrieval-Augmented Generation in Education

Teixeira et al. [13] surveyed RAG technologies, recommending RAG-augmented LLM chatbots to mitigate hallucination in domain-specific educational queries. Neumann et al. [11] developed MoodleBot, an LLM-driven chatbot integrated into an LMS using RAG, achieving 88% accuracy across 46 students with high perceived usefulness. Maalaoui and Samet [12] integrated a RAG-based AI chatbot into a project module for first-year engineering students, finding improved engagement, comprehension, and overall performance.

E. Learning Analytics Dashboards

Xin et al. [8] conducted a pedagogical intervention with 325 undergraduates, finding through propensity score matching that dashboard viewing frequency positively correlates with learning engagement. Cabral et al. [9] presented an AI-powered LAD achieving predictive accuracy scores exceeding 95% across three engineering courses. Safsouf et al. [10] introduced TaBAT, a dashboard tool supporting learner self-regulation and teacher monitoring across different LMS platforms.

F. Personalised and Adaptive Learning

Rekha et al. [15] showed that AI algorithms processing student performance data can pinpoint individual strengths and weaknesses to produce tailored educational content. Wei et al. [14] found a 16.2-point mean achievement gain for students in personalised AI learning path systems versus 7.1 points in conventional groups. Shashanka et al. [16] confirmed that smart tutoring and adaptive learning systems provide personalised dynamic experiences that enhance engagement and promote self-directed learning.

III. METHODOLOGY**A. Overview**

The proposed AI-Powered Learning Management System (AI-LMS) is a web-based application that addresses the key limitations identified in the literature survey. It integrates learning content management, automated assessment, intelligent AI tutoring, multilingual interaction, and real-time visual analytics into a single deployable platform. The system supports two user roles: Administrator (instructor) and Student, each with role-specific dashboards and access controls.

Unlike existing LMS platforms that deliver uniform content to all students, the AI-LMS personalises the learning experience through individual performance tracking, subject-wise smart recommendations, and AI-driven doubt resolution. The system is built entirely on open-source technologies, making it economically feasible for resource-constrained academic institutions.

B. Comparison with Existing Systems

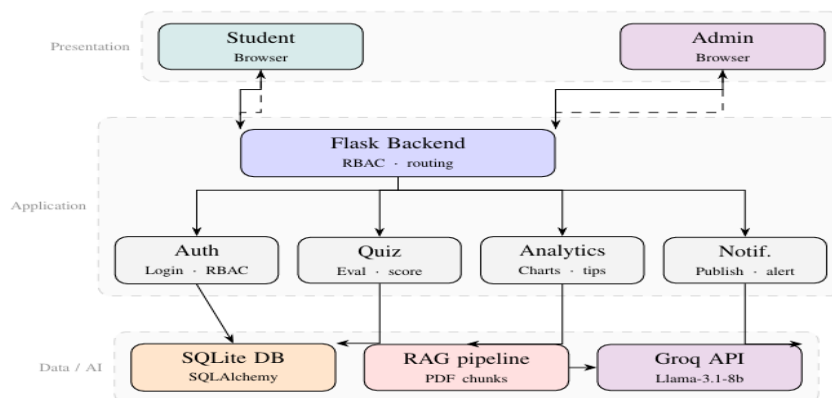
Table I compares the proposed AI-LMS with existing learning management systems across key functional dimensions.

Feature	Existing System	Proposed AI-LMS
Learning Approach	Static, uniform delivery	Adaptive and personalised
AI Tutor	Not available	LLM-powered (Llama-3.1-8b)

PDF Q&A	Not supported	RAG-based contextual chat
Quiz Evaluation	Manual or basic	Automated with instant result
Analytics Dashboard	Score only	Charts, progress bars, tips
Multilingual Support	Not supported	Supported via Groq API
Student Monitoring	Limited	Activity logs and admin panel
Notification System	Basic or absent	Publish-triggered alerts
Technology	Traditional LMS	Flask, SQLite, Chart.js

Table I: Comparison of Existing Systems and Proposed AI-LMS**C. System Architecture**

The AI-LMS adopts a three-tier web architecture. The Presentation Layer delivers role-differentiated dashboards through a Bootstrap-based responsive interface rendered via Jinja2 templates, with Chart.js for client-side visualisation. The Application Logic Layer is a Flask application handling authentication, material management, quiz management, AI tutoring, analytics, and notification dispatch with role-based access control. The Data and AI Services Layer consists of an SQLite database managed through SQLAlchemy, the Groq API (Llama-3.1-8b-instant), and a local PDF processing pipeline for RAG retrieval.

**Fig. 1: System Architecture of the AI-LMS****D. AI Tutor and RAG Module**

The AI tutor operates in two modes. In general mode, students submit free-text questions forwarded to the Groq API with a role-specific system prompt. In PDF chat mode, the system extracts text from the selected study document, segments it into overlapping chunks, and retrieves the most semantically relevant chunks before invoking the model. This RAG approach grounds responses in course-authorised materials, reducing hallucination and ensuring contextually relevant answers. Language selection is preserved across sessions, enabling multilingual support.

E. Quiz and Notification Workflow

Quizzes are created in a draft state, allowing iterative question authoring without triggering student notifications. Publication is an explicit administrator action that sets the quiz status and dispatches per-student notifications simultaneously. Upon quiz submission, the system evaluates answers automatically, calculates scores, and persists results with timestamps for analytics.

F. Analytics Module

The analytics module groups quiz results by subject and computes percentage scores per subject. An overall performance score is derived as the ratio of total marks earned to total marks available. These values are rendered via Chart.js as progress bars, line charts for score trends, and bar charts for percentage comparison. Personalised study tips

and smart recommendations are generated by comparing subject scores against a configurable proficiency threshold using rule-based templates.

IV. RESULTS AND DISCUSSION

A. Functional Testing

All core modules were exercised against ten primary test cases covering student authentication, material access, quiz attempt, AI tutor interaction, PDF chat, analytics rendering, and admin operations. All ten test cases passed. Boundary cases including empty quiz submission, questions exceeding 500 characters, multiple sequential quiz attempts, and unsupported file uploads also passed. Table II summarises the test results.

ID	Scenario	Expected Output	Result
TC-01	Student login (valid)	Dashboard loaded	Pass
TC-02	Student login (invalid)	Error message shown	Pass
TC-03	View study material	Subject content displayed	Pass
TC-04	Quiz attempt and submit	Score generated	Pass
TC-05	Score calculation accuracy	Correct score computed	Pass
TC-06	AI tutor free-text query	Relevant AI response shown	Pass
TC-07	PDF chat query	Context-grounded reply returned	Pass
TC-08	Analytics rendering	Charts and bars displayed	Pass
TC-09	Admin login (valid)	Admin dashboard loaded	Pass
TC-10	Admin material upload	Material visible to students	Pass

Table II: Functional Test Case Results

B. Security Testing

Four security scenarios were evaluated. Students attempting administrator routes received 403 responses without information leakage. Simulated session-token reuse was blocked by server-side validation. SQL injection payloads in login and search fields were neutralised by SQLAlchemy parameterised queries. Role privileges were correctly segregated across all tested workflows.

C. Performance Testing

Concurrent load was simulated with 25 simultaneous student sessions. Table III reports the key performance metrics observed.

Metric	Observed Value
Average page response time	< 200 ms
Quiz submission latency	< 1 second
AI tutor response latency	1 to 2 seconds
Maximum concurrent users tested	25 users
Quiz records without degradation	1,000+

Table III: Performance Benchmark Results

The sub-second quiz evaluation latency results from the in-process Python evaluation loop and a single parameterised database write. AI tutor latency reflects network transit to the Groq API. The 88% course-related accuracy reported for MoodleBot [11] provides a relevant external benchmark for the RAG-grounded AI tutor.

D. Usability Observations

Qualitative observation confirmed that sidebar navigation, role-specific dashboard cards, and inline notifications were interpretable without prior training. Progress bars and Chart.js visualisations conveyed subject-wise performance without additional explanation, consistent with findings from Xin et al. [8] on the positive relationship between intuitive LAD design and student engagement.

V. CONCLUSION

This paper described the AI-LMS, a web application bringing together role-based content management, automated quiz evaluation, LLM-backed intelligent tutoring with RAG-grounded PDF chat, multilingual interaction, and subject-level visual analytics into one deployable system. Building on open-source components keeps licensing costs at zero while meeting the technical and operational constraints of resource-limited academic institutions.

All ten functional test cases passed, four simulated security attacks were blocked without data leakage, and the system maintained sub-200 ms page response under 25 concurrent users. The RAG module tackles the hallucination problem of plain LLMs [13] by anchoring responses to uploaded course materials, while the analytics dashboard gives students visibility into their own progress [10] and equips instructors with data for early intervention [9].

Future directions include adaptive learning paths that dynamically adjust material sequencing based on longitudinal performance modelling [14], predictive risk analytics to flag at-risk students early [9], a voice interface for accessibility, mobile application development, and blockchain-anchored certificates for assessment integrity.

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