

AI Powered Personalized Learning Path Generator

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Abstract: Traditional university systems often decouple attendance tracking from academic support, resulting in delayed interventions and the oversight of critical behavioral warning signs such as chronic absenteeism. To address this gap, this paper introduces an integrated framework combining secure, AI-driven attendance monitoring with personalized educational mechanisms. By treating attendance data as an essential academic indicator, our proposed system employs advanced facial recognition, liveness detection, geofencing, and secure token authentication to ensure precise tracking. Artificial intelligence algorithms analyze these metrics to identify at-risk student patterns, automatically generating customized study pathways aligned with the core curriculum. These adaptive pathways seamlessly integrate targeted educational content and continuous reassessment. Developed upon a robust microservices architecture utilizing Spring Boot and FastAPI, the platform delivers highly scalable and automated student interventions. Experimental results demonstrate that this holistic approach significantly boosts student motivation, mitigates academic failure risks, and accelerates the remediation process through timely, data-informed assistance.

Keywords: Artificial Intelligence in Education, Personalized Learning Path, Automated Attendance Monitoring, Microservices Architecture.

1. INTRODUCTION

The integration of attendance tracking and academic support systems is still a significant factor in the progress and participation of students in modern

educational institutions. The main focus of attendance tracking in attendance systems is on quizzes and assignments, while learning platforms prioritize academic tasks, leading to missed early signs of academic decline.

The presence of frequent absences can be useful in determining the level of engagement and learning gaps, making attendance figures particularly helpful. A large number of systems do not make effective use of this data. At the same time, AI-based learning tools usually react only after performing poorly and missing early warning signals.

An AI-powered closed-loop framework that combines attendance monitoring with personalized learning is presented as a solution to the gap. It is regarded as an active academic sign to trigger intervention.

A microservices architecture is utilized in the system, which includes Spring Boot for backend functionality and FastAPI to handle AI processing, as well as secure multi-factor attendance verification. AI creates learning paths that are aligned with the syllabus by incorporating resources, exercises and performing re-evaluations when risks are identified.

Generally speaking, the framework involves a gradual process of identification, diagnosis, prompt intervention, and modification, creating optimum and strategic academic support system.

2. RELATED WORK:

Research in intelligent educational systems has mainly moved forward in three areas: automated attendance systems, adaptive learning platforms, and AI-based tutoring solutions. Although each area has made

significant progress on its own, bringing them together into a single, closed-loop academic intervention system is still largely absent.

2.1 Automated Attendance Monitoring Systems:

The use of RFID cards and barcodes was utilized in early attendance systems to decrease manual labour.

The presence of proxy attendance was a common issue with these systems, making them efficient but demanding of additional hardware.

As computer vision technology improved, facial recognition systems started to be used on a large scale, using deep learning models like CNNs. As automation was improved, they introduced issues such as spoofing attacks, lighting sensitivity, and privacy concerns regarding biometric data. The use of liveness detection and multi-factor authentication has been a recent solution to these challenges. Yet many systems only verify attendance and these data are not used for academic analysis.



Fig.1. Automated Attendance Monitoring Systems

2.2 Adaptive Learning and Intelligent Tutoring Systems

Adaptive learning systems aim to model students according to their level of knowledge and adjust content accordingly. (A) Traditional methods such as BKT, IRT or rule-based sequencing estimate mastery are used to assess performance in a quiz and then difficulty is adjusted according to the results.

New models like Deep Knowledge Tracing (DKT) are based on neural networks and have evolved over time to analyze performance trends and predict future outcomes. There have been efforts to improve the delivery of content by incorporating reinforcement learning.

Most systems rely heavily on assessment data and neglect behavioural indicators such as attendance and

engagement. However, some exceptions exist. Often, they limit flexibility and personalization by relying on fixed content libraries.

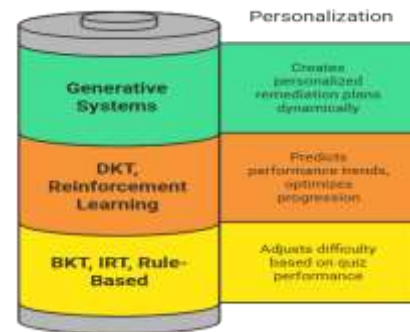


Fig.2. Adaptive Learning and Intelligent Tutoring Systems

2.3 Large Language Models in Education

Large language models (LLMs) have caused a shift in educational technology. Why? These models are commonly employed in AI tutoring systems, automated feedback tools, and content generation platforms. Creating explanations, practice questions, and summaries is effortless with little setup required.

Nevertheless, the majority of LLM-based systems function as reactive resources that only respond when students inquire. Institutional syllabi are often not in line with their recommendations, and they may not accurately identify specific learning gaps.

In addition, their access to secure academic settings is still restricted. Their reliability in structured educational settings is compromised by factors like hallucination, contextual unease, and the absence of performance-based feedback loops.

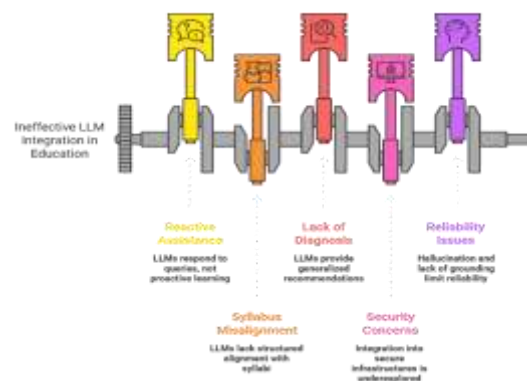


Fig.3. Large Language Models in Education

2.4 Learning Analytics and Academic Risk Prediction

In addition to personalization research, learning analytics studies have examined correlations between attendance and performance, dropout prediction models, and engagement metrics. The use of logistic regression, decision trees, and ensemble models has enabled the identification of students at risk through machine learning methods. While these studies can detect academic risk patterns, the intervention mechanisms are frequently external or manual. Analytics applications often create dashboards or alerts but don't set up personalized remediation plans automatically.

Predictive analytics' practical use in institutional settings is limited by the separation between detection and intervention.

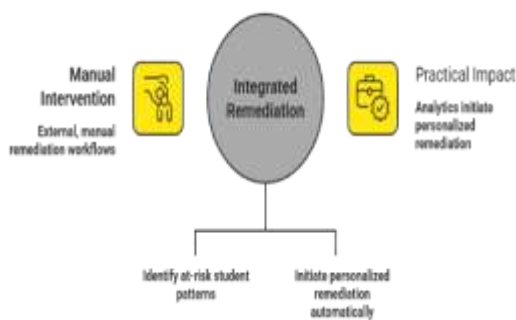


Fig.4. Learning Analytics and Academic Risk Prediction

2.5 Identified Research Gap

Several significant shortcomings exist within present educational systems. Attendance systems and personalized learning platforms are distinct in their operation, whereas adaptive models rely on assessment data for guidance rather than behavioural signals such as absenteeism. Typically, LLM-based tools do not incorporate continuous feedback and syllabus alignment, and predictive analytics seldom prompts automated intervention. Furthermore, only a handful of solutions offer scalable, microservices-based architecture that incorporates secure attendance, AI-driven personalization, and academic analytics. Such gaps emphasize a need for an integrated system treating attendance as academic signalling, with diagnostic intelligence interwoven in the integration of generative AI within scalable, secure systems.

The proposed study develops a framework that employing artificial intelligence and closed-loop technology, which reconciles attendance verification with personalized learning paths and continuous performance evaluation.

3. PROBLEM DEFINITION AND RESEARCH OBJECTIVES

3.1 Problem Definition

The advancement of educational technology does not guarantee the rapid delivery of academic aid to students. Attendance systems and learning platforms work in isolation, with one system monitoring presence while the other concentrates solely on performance and disregarding behavioural clues like absenteeism.

Attendance data is not fully utilized, interventions are delayed due to this and support is provided through generic support. Currently, there are no reliable, automated, or scalable solutions

Key Challenge:

In what ways can attendance data be correlated with risk detection and AI-driven learning to optimize early academic intervention?

3.2 Research Objectives

To address the identified problem, this research defines the following primary and secondary objectives:

Primary Objective

Develop and scrutinize an AI-driven, microservices-based system that combines secure attendance with personalized learning and continuous evaluation.

Secondary Objectives

1. Construct a safe attendance mechanism that incorporates facial recognition, liveness detection, geofencing, and token authentication.
2. Optimise attendance by providing actionable signals for automated response generation.
3. Develop a learning path generator that aligns with the syllabus, using knowledge mapping and LLMs.
4. Utilize adaptive learning that considers performance and weaknesses.
5. Establishing a closed loop system involves detection, diagnosis and intervention before adaptation.

6. Assess performance by evaluating grades, engagement levels and risk reduction.
7. Foster scalability and security by implementing a microservices architecture (Spring Boot, FastAPI, databases).

3.3 Research Hypotheses

The proposed framework is substantiated by the study's hypotheses:

- **H1:** Using AI-generated personalized learning paths, students experience significant improvement in their post-assessment scores when compared to traditional meth.
- **H2:** Academic risk reduction is more effective with attendance-based interventions than performance-only systems.
- **H3:** A closed-loop framework known as H3 enhances student engagement and completion rates by removing the need for static model recommendations.

4. PROPOSED SYSTEM ARCHITECTURE

4.1 Architectural Overview

This system is a microservices, closed-loop academic framework that integrate[s] secure attendance management with AI personalized learning. By utilizing various technologies, it implements polyglot architecture to optimize performance across components.

Unlike monolithic systems, the design separates core functionality such as business logic, AI processing, and presentation, allowing for scalability, flexibility, ease of maintenance, etc.

The three primary layers comprise the structure:

1. Attendance & Security Layer.
2. AI Personalization Layer.
3. Analytics & Governance Layer.

Asynchronous processes and secure APIs facilitate communication between layers, resulting in a continuous academic feedback and recovery system.

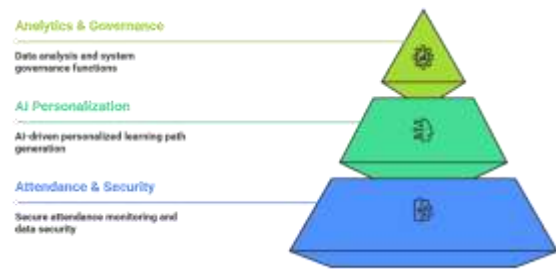


Fig.5. Proposed System Architecture

4.2 Microservices Design Philosophy

The microservices architecture is designed to be flexible and scalable:

- Service Decoupling enables Attendance to be independent from AI modules.
- At Polyglot Design, Spring Boot (Java) is responsible for security and backend logic, while FastAPI(python), the AI functionality takes over.
- Scalability is not a prerequisite for AI services to be scaled independently from their core systems.
- Failure of a service does not affect the other services; they are fault isolated.

To ensure uniform versioning and efficient deployment, all services are managed in a single monorepo.

4.3 Core Components

4.3.1 Short-lived and Humane Attendance and Security Service

The module is responsible for authentication, attendance recording, and system administration:

- JWT-based authentication.
- Facial verification handling.
- GPS-based geofencing validation.
- Dynamic QR/token-based authentication.
- Attendance storage in MySQL.

Attendance Verification Workflow

1. Student marks attendance via web/mobile.
2. The facial image is recorded and authenticated.

3. Liveness detection ensures real presence.
4. GPS confirms location.
5. Token validation prevents misuse.
6. The database contains verified information.

The use of this multi-layered approach guarantees secure, dependable, and proxy-resistant attendance without the need for additional hardware.

4.3.2 The AI Personalization Service (Fast API)

It is an AI microservice that handles core intelligence and personalization functions:

- Face recognition and liveness detection
- Weak topic identification.
- LLM-based learning path generation
- Adaptive difficulty adjustment
- Structured remediation planning.

Data Storage (MongoDB):

- Generated learning paths
- Remediation history.
- Diagnostic and analytics data.



Fig.6. Core Components

4.4 Knowledge Mapping Model

A knowledge mapping framework is utilized by the system to produce output that is structured and aligned with the syllabus, using a JSON topic graph:

- Course → Units → Subtopics → Resource references

Prior to invoking the AI, a weak area is mapped to this graph when s/he misses - or performs poorly. It preserves the relevance of generated content while preventing unproductive or irrelevant results.

4.5 AI Learning Path Generation Engine

The learning path generation is structured in a way that:

1. **Assessment:** Investigate potential weaknesses based on performance and attendance issues.
2. **Formulation:** Merge ineffective areas, previous scores with a syllabus context.
3. **Structured Output Generation:** A step-by-step roadmap for AI is created, which includes:
 - Concept resources.
 - Practice tasks.
 - Exercises/assessments.
 - Reassessment checkpoints.
4. **Monitoring:** The generated route is saved and associated with the student to track their progress.



Fig.7. AI Driven Learning Path Generation Engine

4.6 The Short-Loop Academic Recovery Model

It is based on continuous feedback:

Detection → Diagnosis → Path Generation → Execution → Reassessment → Adaptation

Based on reassessment results:

A rise in performance leads to an improvement of mastery.

Where gaps exist, you have a better learning path.

Unlike static model recommendations, the system is designed to enable continuous improvement through this dynamic cycle.

4.7 The Analytics and Governance Layer

Attendance, performance and remediation data are gathered at the analytics layer and output:

- Attendance-performance insights.
- At-risk student alerts.
- Absenteeism trends.
- Remediation effectiveness metrics.

Real-time monitoring through faculty dashboards and automatic alerting facilitate intervention.

4.8 Security and Data Management

Security is ensured through:

- Role-based access control.
- JWT-secured APIs.
- Encrypted database connections.
- Token-based attendance validation.
- Separation of structured and unstructured data (MySQL)

This platform facilitates scalability and continuous integration by providing Docker-based deployment and CI/CD pipelines.

4.9 System Workflow Summary

The system workflow follows:

1. Secure attendance verification.
2. Attendance analysis for patterns.
3. Detection of weak academic signals.
4. AI-based learning path generation.
5. Reassessment of student performance.
6. Analytics updates and monitoring.

This system of integrated monitoring and intervention creates an intelligent and proactive academic environment.

5. METHODOLOGY

5.1 Methodological Overview

This proposal involves a closed-loop academic model that incorporates automated attendance monitoring and an AI-driven personalized learning system. The system combines computer vision, geolocation validation, generative AI, and learning analytics to identify academic risks and offer personalized assistance.

It uses a well-structured pipeline of verification and behavioural data collection, identification of weak knowledge areas, generation of learning paths using AI, and continuous reassessment with adaptation. These stages are used together to transform raw academic data into actionable and personalized learning interventions.

5.2 The Attendance Verification System

To prevent the need for proxy attendance, attendance verification relies on a multi-layered software approach to guarantee accuracy. Facial recognition, liveness

detection, geolocation validation, and dynamic token authentication are utilized to authenticate student identity and presence

The values of F include facial similarity, L liveness confidence, G geolocation validation, and T token authentication status. The overall verification score is:

Attendance verification probability A_v can be expressed as:

$$A_v = w_1F + w_2L + w_3G + w_4T$$

Where:

- w_1, w_2, w_3, w_4 represent normalized weights for each verification factor. Attendance is marked valid when:

Where τ is a predefined authentication threshold.

Enhanced reliability and reduced chances of spoofing, such as proxy attendance, remote access, or token misuse, are achieved through this layered model.

5.3 Weak Knowledge Area Detection

Quiz performance and attendance behaviour are the only indicators of a person's weak knowledge detection.

Let:

- S_i represent the student score for topic i
- T_i represent the mastery threshold for topic i

A topic is classified as weak if:

$$S_i < T_i$$

Additionally, absence from a lecture covering topic i increases the probability of knowledge gaps.

A Weak Topic Index (WTI) is computed as:

$$WTI_i = \alpha (T_i - S_i) + \beta A_i$$

Where:

- A_i represents absence indicator (1 if absent, 0 if present)
- α, β represent weighting parameters.

Personalized remediation is given preference to areas with higher WTI values.

5.4 Model of Knowledge Mapping

A knowledge graph is used by the system to map AI-generated learning paths and keep track of it, showing course sequences from a given syllabus. The backend stores the hierarchy in a JSON-based syllabus model.

Before the AI is invoked, nodes from this graph are picked up by the system if weak topics are detected. It keeps the generated content factually true to itself, relevant to readers, and free from any unrelated or arbitrary outputs.

5.5 AI Learning Path Generation Algorithm

The Humanized + Shortened Algorithm for AI Learning Path Generation.

FastAPI service-integrated LLM fuels the learning path generation. It starts with a contextual input, which is made up of subpar topic tags, past performance data, and syllabus references.

A structured learning plan that includes concept resources, practice tasks, exercises, and reassessment checkpoints is created by the model using this input. The JSON output is formatted in a stepwise manner to ensure consistency and easy tracking.

5.6 Closed-Loop Academic Recovery Algorithm

A closed-loop remediation process is employed by the system:

$D \rightarrow G \rightarrow E \rightarrow R \rightarrow U$

Where:

D = Detection of weakness

G = Generation of learning path

E = Execution by student

R = Reassessment of learning outcomes

U = Update of student knowledge state

If the reassessment score exceeds the mastery threshold:

$Score_{new} \geq \text{Threshold}$

the topic is marked as mastered.

Otherwise, it becomes part of an improved learning path with modified difficulty. Continuous repetition fosters adaptive and ongoing learning advancement.

5.7 Learning Progress Evaluation

Student improvement is evaluated using performance difference:

$$\Delta P = Score_{post} - Score_{pre}$$

Where:

$Score_{pre}$ represents the initial assessment score

$Score_{post}$ represents the score after remediation.

Positive ΔP indicates effective intervention

5.8 Algorithm Summary:

The overall process involves attendance verification, recording data, detecting weak topics, creating AI-based learning paths, managing student enrolment, reviewing data and more.

6. EXPERIMENTAL SETUP AND EVALUATION

6.1 Experimental Setup

A controlled academic setting was used to test the system's performance in a real-life classroom setting. A 4-week trial was conducted with 40 students across a range of topics.

It deployed the framework in a microservices architecture, with Spring Boot handling authentication and attendance and managing data. Structured information was sourced from MySQL, while MongoDB stored learning paths and remediation records generated by AI.

The system utilized a web dashboard for students to log in and track attendance using facial verification from utilizing webcams, as well as geolocation and dynamic token authentication.

6.2 Evaluation Strategy

It assessed a classic system against the suggested artificial intelligence model:

The existing baseline system lacked personalized assistance, but the proposed approach involved AI-based attendance verification, personalized learning paths, and closed-loop remediation. Additionally, standard attendance tracking was not available for this purpose.

Two groups of 20 students were chosen: a control group using the traditional system and an experimental group with the AI-based system.

6.3 Evaluation Metrics

The system performance was evaluated using the following metrics:

1. Attendance Accuracy

Measures correctness of attendance marking:

$$Accuracy = \frac{Correctly\ Marked\ Attendance}{Total\ Attendance\ Attempts}$$

2. Proxy Reduction Rate

Measures effectiveness of anti-spoofing mechanisms:

$$Proxy\ Reduction = \frac{Detected\ Proxy\ Attempts}{Total\ Proxy\ Attempts}$$

3. Detected Proxy Attempts

$$Learning\ Gain = Score_{post} - Score_{pre}$$

Where:

- $Score_{pre}$ = score before remediation
- $Score_{post}$ = score after AI learning path

4. score after AI learning path

Measured using:

- Learning path completion percentage
- Number of revisits to study material

5. Academic Risk Reduction

Percentage decrease in students below performance threshold.

6.4 Implementation Conditions

The two groups were assessed using the same syllabus and assessment structure, with equal study time and difficulty levels. Both groups received fair evaluation. All experiments were conducted under controlled conditions to ensure uniformity.

6.5 System Workflow During Evaluation

Attendance was recorded at the beginning of each session during the evaluation process. We found that students with low grades or frequent absences were

included, and the experimental group was given AI-generated learning paths. Students were re-assessed once they had completed the assigned tasks, and their performance and engagement levels were reported.

6.6 Evaluation Objective Summary

This evaluation would also assess accuracy of attendance verification, effectiveness of proxy prevention, the impact of AI-driven learning paths on performance and improvements in student engagement and academic recovery.

7. RESULTS AND DISCUSSION

7.1 Attendance System Performance

Testing showed the multi-layered attendance system was highly reliable. The integration of facial recognition, liveness detection, geofencing, and token validation resulted in a significant improvement in accuracy and security.

It also proved to be 96.5% more accurate than conventional single-factor methods and cut down proxy attempts by about 92%. Consequently, attendance data became more consistent and credible.



Fig.8. Attendance System Performance

7.2 Learning Performance Improvement

The effectiveness of AI-generated learning paths was assessed using pre- and post-assessment scores.

From there, the average improved to 74% from 58.6% and learning increased by 16%. In contrast, there was only slight improvement in the control group, indicating that personalized AI-driven remediation is still effective.

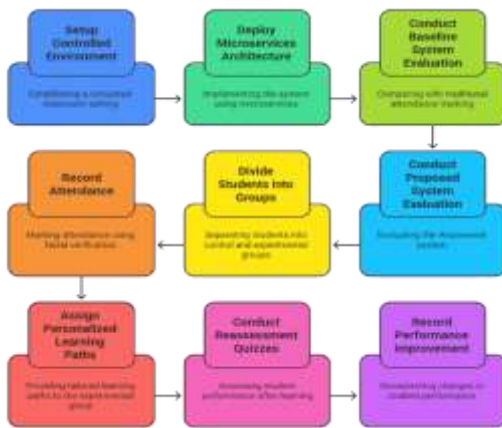


Fig.9. Learning Performance Improvement

7.3 Engagement Analysis

The experimental group experienced a significant surge in student engagement.' A 78% average of learners completed their learning paths, with a higher frequency of revisiting weak topics and more active participation in reassessment.

These results suggest that personalized content fosters greater motivation and a more consistent learning experience.

7.4 Academic Risk Reduction

This system has effectively reduced the risk of academic misconduct. After intervention, the proportion of students falling below performance thresholds decreased from 35% to 18%.

The improvement indicates that the combination of attendance-based early detection and AI assisted support facilitates efficient and timely academic recovery.

7.5 Comparative Analysis

Metric	Baseline System	Proposed System
Attendance Accuracy	85–88%	96.5%
Proxy Detection	Low	High (92%)
Learning Improvement	Minimal	+16%
Engagement Rate	Moderate	High
Risk Reduction	Limited	Significant

The results clearly demonstrate that combining attendance intelligence with AI-driven personalization provides measurable advantages over traditional systems.

7.6 Discussion

The findings demonstrate the usefulness of integrating AI-driven learning systems with behavioural signals, such as attendance. Instead of treating these separately, the proposed framework links student involvement directly to academic intervention.

Compared to generic methods, targeted, weak-topic-based remediation yields better performance outcomes. Structured learning paths are believed to enhance participation and consistency due to their high levels of engagement. Unlike static models, this system is also closed-loop so it can be monitored continuously and changed dynamically.

However, some limitations exist. Facial recognition can be affected by poor lighting conditions, and the effectiveness of learning paths depends on accurate detection of weak topics and prompt design. These areas are conducive to further development.



Fig.10. Final Result & Discussion

8. CONCLUSION

This research proposes a closed-loop, AI-powered academic framework that incorporates secure attendance monitoring and personalized learning. It views attendance as an early warning system, unlike most systems.

The system integrates multi-factor verification with AI-driven, syllabus-aligned learning paths to provide adaptive and targeted support. Attendance reliability,

engagement, and academic performance improvements were observed in experimental studies.

9. FUTURE WORK

While this proposed system does provide some advantages, there are several aspects to be explored in subsequent studies. The development of a mobile app that is dedicated can improve accessibility by providing real-time attendance tracking and learning path access. Through the use of advanced personalization and reinforcement learning, long-term student behaviour can be used to further optimize learning paths.

Behavioural analysis or facial analysis could be used to incorporate emotion and engagement detection, potentially providing more comprehensive information on student learning patterns. Decentralized cloud infrastructure allows the system to be scaled effectively for large institutions. Also, the implementation of transparent AI through explainable AI can enhance transparency by elucidating learning pathways. By incorporating multilingual support, the system can be made more accessible to different learners.

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