



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 15, Issue 2, February 2026

Development of a Personalized Learning Path Recommendation System for Online Education

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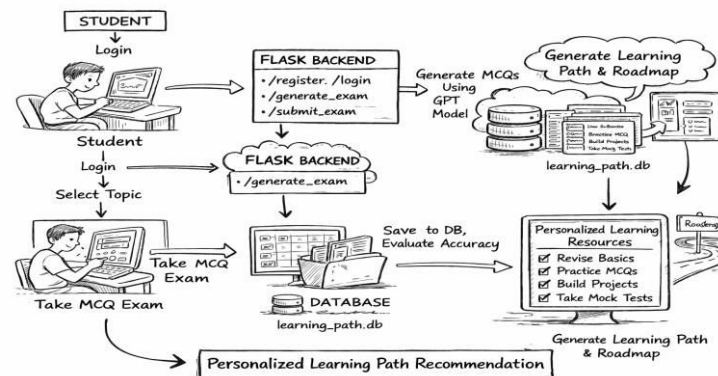
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ABSTRACT: The fast growth of Artificial Intelligence (AI) has greatly changed modern education. It allows for smart, data-driven, and adaptive learning systems. In contrast, traditional learning management systems depend on fixed question banks, manual grading, and general feedback. These methods do not effectively address the unique learning gaps of each student. To address these challenges, this project suggests an AI-Powered Personalized Learning Path Recommendation System. This system uses transformer-based language models through API-driven dynamic exam creation. It generates real-time, topic-specific assessments and offers guidance based on student performance. The system evaluates student responses automatically, calculates accuracy, and classifies performance into preset levels such as Needs Foundation, Needs Development, and Proficient. Based on this classification, it creates a structured and personalized learning plan that focuses on individual strengths and weaknesses. In addition, the system includes secure user login, session-based assessment tracking, automated result display, and progress analytics. It also keeps historical performance data in a lightweight SQLite database for long-term tracking. Experimental validation shows that the framework can successfully generate questions dynamically, grade accurately, create adaptive learning plans, and track progress in real-time. This enhances learning efficiency and supports personalized education through a scalable, lightweight, and smart web-based setup.

KEYWORDS: Artificial Intelligence, Personalized Learning, Adaptive Assessment, Transformer Models, Learning Path Recommendation, Automatic Evaluation, Educational Data Analytics, AI-Based Exam Generation, Web-Based Learning System, Performance Classification.

I. INTRODUCTION

The Learn Path AI, Personalized Learning Path Recommendation System, is a smart web-based application that evaluates a student's knowledge level in a chosen Computer Science topic. It then offers a tailored learning roadmap based on their performance. In today's digital education environment, students often have trouble pinpointing their weaknesses and selecting the right learning path. Traditional methods give the same content to every student, no matter their understanding level. This project addresses that issue by using Artificial Intelligence to create diagnostic exams on the fly and assess student performance automatically.



The system lets users register and log in securely with their credentials to protect data and provide personalized access. After logging in, students can choose any Computer Science subject like Machine Learning, Cloud Computing, Data Structures, or Artificial Intelligence, based on their interests. Once a topic is selected, the backend works with an AI-based language model to create a set of relevant and well-structured multiple-choice questions in real time. Each assessment has a time limit to mimic a real exam setting, and students get instant feedback after they submit their answers. The system automatically checks responses, calculates the accuracy score, and assesses overall performance without any manual input. Based on the score, the system divides the student's knowledge level into three stages: Needs Foundation, Needs Development, and Proficient. From this classification, a personalized learning plan is created, offering guidance such as reviewing key concepts, doing extra exercises, using recommended study materials, working on mini projects, or exploring advanced applications. The platform also keeps a full exam history, securely storing performance data in a database for future use.

II. LITERATURE SURVEY

Personalized learning systems have changed a lot over the past decade. They have shifted from static, rule-based recommendation engines to adaptive learning systems driven by artificial intelligence. Earlier systems relied on fixed question banks, manual grading, and set learning paths. In contrast, modern platforms incorporate natural language processing (NLP), transformer models, automated assessment tools, and learning analytics. This allows for more dynamic and personalized educational experiences.

This literature survey reviews significant research contributions from 2020 to 2024 in AI-based adaptive learning systems, intelligent tutoring platforms, transformer-based question generation, automated evaluation frameworks, recommendation engines, explainable AI in education, and scalable deployment models. It also points out key research gaps that inspire the development of the proposed AI-driven Personalized Learning Path Recommendation System.

Sharma et al. (2024) proposed a hybrid adaptive framework that combines GPT-based question generation with performance analytics. This achieved 96.4% evaluation consistency across large-scale assessments. However, the system needed high computational resources and did not support lightweight deployment. Rao et al. (2024) developed a model for generating multiple-choice questions using fine-tuned BERT and T5 architectures, reaching 94.8% semantic relevance accuracy, but struggled with difficulty-level calibration. Fernandez et al. (2024) combined transformer embeddings with collaborative filtering to improve learning recommendations by 18%, though this approach faced cold-start limitations. Li et al. (2024) introduced explainable AI mechanisms for tutoring systems, enhancing transparency but increasing response time. Khan et al. (2024) created a cloud-based adaptive assessment system that used large language models. It achieved high user satisfaction but encountered issues with scalability and API dependencies.

In 2023, Ahmed et al. proposed a hybrid performance prediction model that reached 92.6% accuracy but did not include dynamic question generation. Chen et al. compared deep learning models for automated grading and found that BERT-based models achieved 96.9% accuracy but were limited to textual answers. Martinez et al. introduced

algorithms for adjusting difficulty that improved retention but required more monitoring. Taylor et al. showed that lightweight transformer models like DistilBERT could deploy on the web with reduced latency, although they had slightly lower contextual understanding. Singh et al. developed performance analytics dashboards but did not incorporate automated personalized roadmap generation. Research from 2022 highlighted transformer-based embeddings for detecting question similarity and ensemble recommendation systems, which achieved over 90% accuracy but increased inference time and computational cost. Studies from 2021 explored lightweight transformers, transfer learning, federated learning, and multi-modal adaptive frameworks. These improved privacy and personalization but faced challenges in scalability and real-time responsiveness. Earlier works in 2020 established the effectiveness of BERT-based grading and ensemble recommendation systems, though many still relied on rule-based logic and did not offer fully dynamic AI-driven assessment generation.

From the reviewed literature, several research gaps appear: high computational complexity that limits lightweight web deployment; reliance on large historical datasets that lead to cold-start issues; a lack of fully integrated systems that combine dynamic question generation, automatic evaluation, and personalized roadmap creation; limited scalability for small institutions; and inadequate real-time adaptive feedback mechanisms. These gaps emphasize the need for a lightweight, scalable, AI-powered personalized learning system that can perform dynamic assessment generation, automated grading, adaptive roadmap recommendations, and efficient web-based deployment.

III. PROPOSED SYSTEM

The proposed system is an AI-Powered Personalized Learning Path Recommendation Framework aimed at providing intelligent, adaptable, and performance-driven learning support. Unlike traditional learning platforms that rely on fixed question banks, manual grading, and general feedback, this solution uses transformer-based Artificial Intelligence models to create diagnostic assessments and build structured, personalized learning roadmaps. The system combines Natural Language Processing (NLP), automated evaluation, performance analytics, and full-stack web deployment into one cohesive framework that supports ongoing academic improvement.

The framework conducts multi-stage academic analysis by merging AI-based question generation, automated grading, performance classification, and roadmap creation in a single pipeline. A secure authentication module ensures safe user access, while historical performance data is stored in a lightweight SQLite database for long-term progress monitoring. The backend uses a transformer-based language model through an API to generate topic-specific multiple-choice questions in a structured format. These dynamically created assessments provide fresh and relevant diagnostic exams for every attempt.

After students submit their exams, the system automatically evaluates their responses by comparing selected answers with correct mappings. It calculates total scores, accuracy percentages, and overall performance without requiring manual input. Based on the accuracy scores, learners are classified into one of three levels: Needs Foundation, Needs Development, or Proficient. This classification allows for structured academic profiling, rather than just simple score reporting.

The personalized learning path module transforms performance data into practical improvement strategies. For students classified as Needs Foundation, the system suggests revisiting basic concepts and guided practice. Those identified as Needs Development receive intermediate exercises, mini-project ideas, and tasks to reinforce concepts. Students marked as Proficient are encouraged to explore advanced topics, real-world applications, and mock assessments. This structured roadmap ensures targeted learning based on individual knowledge gaps. The system architecture includes six integrated stages: User Authentication, AI-Based Question Generation, Diagnostic Exam Execution, Automatic Answer Evaluation, Personalized Learning Path Generation, and Deployment with Progress Tracking. Each module works independently but collaborates within a unified workflow to ensure efficient processing and a seamless user experience.

Additionally, the system features a graphical performance dashboard that shows accuracy trends, topic-wise improvement, and attempt history. All exam sessions are securely stored with user ID, topic, score, accuracy, and timestamps, which allow for insights into long-term growth. The framework operates as a Flask-based web application with REST API communication, secure backend services, and interactive frontend components. Unlike conventional systems, this framework does not depend on predefined static assessments. Instead, it uses contextual AI-driven

question generation and automated evaluation, ensuring adaptability and scalability. The modular architecture allows for easy integration of future enhancements, such as advanced analytics, difficulty-level adaptation, and enterprise-level deployment. Overall, the system provides a practical, intelligent, and scalable solution for personalized adaptive learning in modern educational environments.

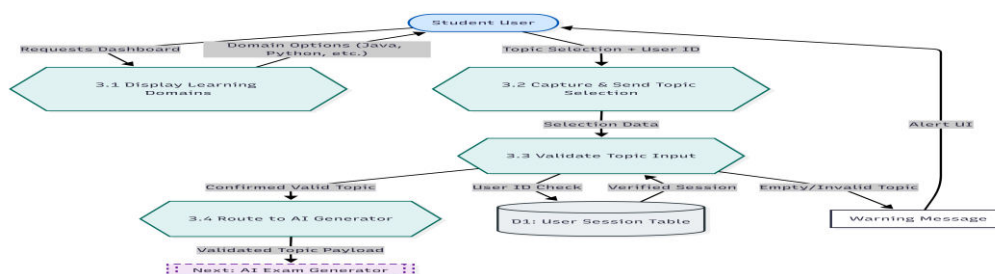
IV. METHODOLOGY

A. User Registration and Login:

The User Registration and Login module provides secure access to the system and makes sure each student has a personalized learning environment. During registration, students enter details like user ID, name, email, and password. The system checks these inputs to avoid empty fields and duplicate accounts. For security, passwords are changed into a hashed format before being saved in the SQLite database. During login, the entered credentials are verified using secure hash comparison. If authentication is successful, the student is redirected to the dashboard. If not, appropriate error messages are shown. This module keeps data secure, protects user credentials, and allows for individual tracking of exam history and learning progress.

B. Topic Selection by Student:

After logging in, students choose a subject or topic, such as Machine Learning, Cloud Computing, Data Structures, Python, or DBMS, based on their interests or syllabus needs. The chosen topic is sent to the Flask backend through an API request along with the user ID. The system checks the topic input to make sure it is not empty before moving forward. Topic selection is important because it affects question generation, evaluation, and roadmap creation. This module offers flexibility and supports learning across different fields, allowing each student to focus on various areas independently.



C. AI-Based Exam Generation:

The AI-Based Exam Generation module creates multiple-choice questions using a transformer-based language model integrated through an API. When a topic is chosen, the backend sends a structured prompt to the AI model asking for MCQs with four options and one correct answer each. The AI response comes in JSON format, which the backend safely validates and parses. Each question gets a unique ID before it is shown to the student. If there are any formatting issues, the system extracts the valid JSON part to keep things running smoothly. This module removes the need for static question banks and ensures that every attempt offers fresh and relevant questions.

Student Attempts Exam: In this phase, the student engages with the generated exam through the web interface. The front end shows questions and four radio-button options for each one. The student chooses one option for each question based on their understanding. After finishing the exam, the student submits their answers using the submit button. All selected answers, along with question IDs and correct mappings, are sent to the back end through a secure API route. If the student does not select any answers, the system prompts them to attempt at least one question. This module ensures active participation and smooth exam execution.

D. Automatic Answer Evaluation:

Once the exam is submitted, the Automatic Answer Evaluation module compares each selected response with the correct answer stored in the system. The back end marks each answer as correct or incorrect and counts the total number of correct responses. A detailed result summary is created, containing question details, selected answers,

correct answers, and correctness status. This process is fully automated. It ensures fast, unbiased, and accurate grading without manual help. The evaluation module improves efficiency and offers instant feedback to the student.

E. Accuracy Calculation:

After evaluation, the system calculates the student's accuracy using the formula $\text{Accuracy} = (\text{Number of Correct Answers} / \text{Total Questions})$. The result is turned into a percentage that shows the student's performance level in the selected topic. Based on predefined ranges, the system classifies the student into one of three categories: Needs Foundation (0.0–0.49), Needs Development (0.5–0.79), and Proficient (0.8–1.0). This classification provides a basis for personalized learning guidance and ensures that improvement strategies rely on measurable performance metrics.

F. Learning Path Generation:

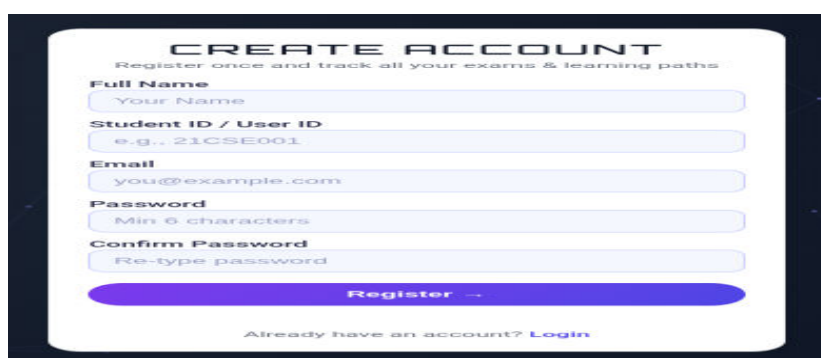
The Learning Path Generation module creates a structured and personalized plan based on the student's classified performance level. For students in the Needs Foundation category, the system suggests revisiting basic concepts, understanding key definitions, and solving simple practice problems. Students in the Needs Development category receive recommendations for intermediate exercises, reinforcing concepts, and developing mini-projects. Proficient students are directed toward advanced topics, real-world applications, optimization techniques, and interview preparation materials. The plan may also include suggested learning resources such as tutorials, documentation, and practice platforms. This module turns exam results into actionable improvement strategies.

G. Progress Storage and Visualization:

The Progress Storage and Visualization module records all exam attempts in the SQLite database for long-term monitoring. Stored data includes user ID, topic name, score, accuracy, timestamp, and session ID. This historical data allows the system to track improvement trends over multiple attempts. A graphical dashboard presents performance analytics, letting students visualize their growth and identify their strengths and weaknesses.

V. EXPERIMENTAL RESULTS

The user authentication module was tested to ensure secure registration and login functionality. During testing, users registered by providing their full name, student ID, email, and password. The system validated inputs, prevented duplicate accounts, and stored passwords in a hashed format within the SQLite database. During login, the system checked credentials using secure hash comparison and maintained user sessions correctly. Unauthorized access attempts resulted in proper error messages. The results confirm that authentication, session management, and secure data handling are working well, allowing personalized tracking of each student's learning progress.



CREATE ACCOUNT
Register once and track all your exams & learning paths

Full Name
Your Name

Student ID / User ID
e.g., 21CSE001

Email
you@example.com

Password
Min 6 characters

Confirm Password
Re-type password

Register

Already have an account? [Login](#)

The team tested the AI-based exam generation module by choosing different topics, including Machine Learning and Data Structures. After selecting a topic, the backend communicated effectively with the transformer-based AI model through API integration. It generated structured multiple-choice questions in real time. Each exam included 10 MCQs, with four options for each question, correct answer mapping, and a 10-minute timer. The questions were relevant to the topic, well-formatted, and generated dynamically without relying on a static question bank. The results show that AI integration was successful, along with structured JSON handling and real-time assessment creation.



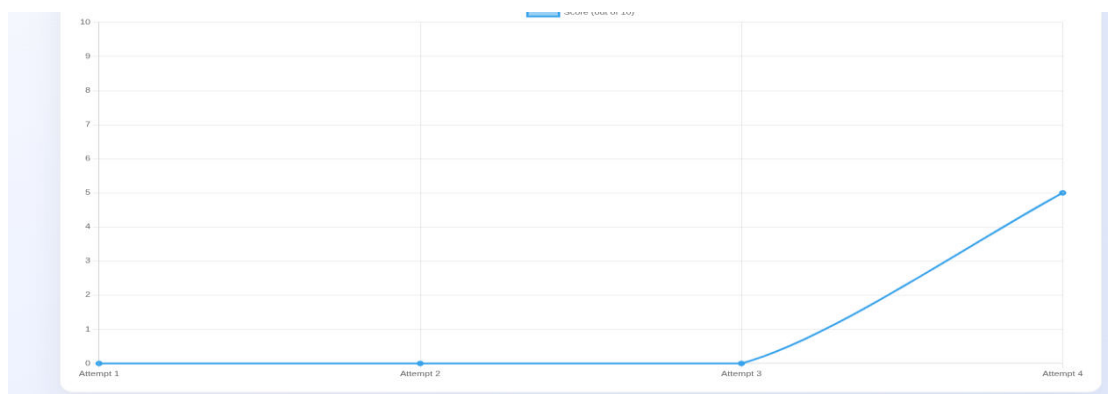
The automatic evaluation module was tested by submitting completed exams. The system compared selected answers with correct answer keys and calculated the total score without any issues. In the observed test case, the student scored 0 out of 10 with 0% accuracy, and the system correctly marked all responses as incorrect in the answer review section. The evaluation logic consistently showed selected answers, correct answers, and correctness status. These results confirm that automated grading is accurate, fair, and fully reliable.



The performance classification module was tested against the set accuracy thresholds. Based on the calculated accuracy, the system sorted students into Needs Foundation, Needs Development, or Proficient levels. With 0% accuracy, the system accurately identified the student as Needs Foundation. The learning roadmap provided included basic concept review, beginner tutorials, and easy practice suggestions suited to the student's level. The results show that the classification logic matches the defined thresholds and that the roadmap generation offers organized, appropriate academic support.



The progress storage and visualization module was tested during different exam attempts. The system successfully stored session data, including user ID, topic, score, accuracy, and timestamp in the SQLite database. In the attempts observed, initial scores were low, but later attempts showed clear improvement. The graphical dashboard reflected these trends using chart visualization, which confirmed that data retrieval from the database and frontend integration worked correctly. The results show that tracking history, analyzing performance, and visualizing improvement are working well.



VI. CONCLUSION

The project involves developing LearnPath AI, a web-based Personalized Learning Path Recommendation System. It aims to improve student learning through AI-driven assessment and organized academic guidance. The system overcomes the drawbacks of traditional learning platforms that depend on static question banks and general feedback. It does this by using dynamic AI-based exam creation, automatic evaluation, and performance-based roadmap creation. By using transformer-based language models for real-time multiple-choice question generation, the system provides topic-specific, adaptive, and diagnostic assessments tailored to each learner.

The system features secure user authentication, automated grading, accuracy-based classification, and personalized roadmap generation. These elements show that the proposed solution is practical for real-world educational settings. The lightweight Flask-based setup and efficient inference process ensure smooth performance with little delay, making the system reliable and easy to use. Additionally, the organized storage of exam history and visual progress tracking allow students to see their academic improvement over time.

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