

Smart-Adaptive: Intelligent Recommendation Systems for Personalized Multi-Platform Learning

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Abstract—Conventional education systems have a standardized teaching methodology which fails to serve the needs of the different students when it comes to their unique learning requirements. The disparities in the level of understanding, previous knowledge, and the speed at which the learner perceives are usually ignored, and they may lead to diminished interest and disproportionate learning results. In order to meet this challenge, the present paper presents a Personalized Learning Platform that could be used in both web and mobile platforms where the material would be adjusted based on performance and learning behavior of the students. The proposed platform is an adaptive learning method based on AI to analyze interaction with students, assessment performance, and progress trends. According to this analysis, the system suggests appropriate learning materials and topics and especially on areas where the learner has been struggling. The platform helps with learning in the form of performance based content delivery, tracking of progress and personalized feedback.

Index Terms—Personalized Learning, Adaptive Learning Systems, Artificial Intelligence in Education, Recommendation Systems, Learning Analytics, Multi-Platform E-Learning.

I. Introduction

Conventional education has provided similar teaching practices to all learners. It assumes that everyone is given the same content to learn regardless of their individual learning pace and performance. This process simplifies the sharing of information but in many cases does not take into consideration the variation in learners. Consequently, this disengages certain of the students and the outcome of their learning is different. The slow learners will lag behind, whereas the advanced students will become bored since they are not challenged adequately. Learning systems need to be adaptable in the sense that they should be able to change the content and instructional pathways based on the behaviour of the learners as Brusilovsky and Millan [1] highlighted. With the help of AI and ML, it becomes possible to create adaptive learning, which analyzes the performance of learners in order to pinpoint the knowledge gaps and provide specific, data based recommendations, assisting not only learners but also the educators without usurping the role of

instruction [2]. The need to incorporate personalization, accessibility and usability in one web and mobile learning platform informs this research. This system will be performance based content adaptation to provide a specific learning experience and ensure consistency among devices. This study suggests developing a personalized learning platform, which is based on AI, to bypass the drawbacks of the traditional and digital education systems due to the possibility of adaptation to the needs of the individual learners. By ensuring adaptive learning and cross-platform designing, the strategy seeks to enhance the interaction and engagement of the learners and encourage scalability and effective learning experiences.

A. Problem Statement

Most existing learning systems adopt a fixed teaching method where the learning content is the same for all students, regardless of their learning progress, learning background, and learning performance. These approaches tend to neglect the individual learning needs of students, leading to poor engagement, retention and learning performance. While online learning systems have made learning more accessible, many systems still lack the real-time personalization and adaptive recommendation features. Thus, a smart learning system is needed to monitor the learning behavior of students, detect areas of weakness and recommend suitable learning resources for both web and mobile platforms.

B. Research Motivation

The increasing popularity of online learning and learning platforms has given rise to new possibilities for learning. Learners now have access to learning content on the internet and mobile devices with convenience. But there are challenges for students to choose the right content based on their knowledge, learning pace and learning objectives. The majority of current systems offer the same content to all learners, regardless of their different needs. Hence, some learners may find the content too hard and others may be bored due to low challenge. This gap leads to a demand for smart recommendations to guide learners in finding suitable learning resources, tests and pathways. This research aims to create an intelligent adaptive system that will enhance engagement, efficiency and learning outcomes via content recommendations.

C. Research Objectives

The main goals of this study are:

- To design and develop an AI-based personalized learning platform for both web and mobile environments.
- To analyze learner performance, behavior, and progress using intelligent data-driven techniques.
- To recommend suitable learning materials, quizzes, and topic sequences based on individual needs.
- To enhance learner engagement, motivation and performance using adaptive learning materials.
- To provide a scalable multi-platform system that ensures a consistent learning experience across devices.
- To ensure privacy, transparency and responsibility while personalizing learning.

II. Literature Review

The concept of adaptive learning and individualized education has gained the attention of researchers because educators and technological experts are trying to eliminate the flaws of the conventional teaching models. The ability of adaptive learning systems to address a wide spectrum of needs of learners has been studied regarding numerous subjects, typically based on data-driven and AI-improved procedures. These articles show that there is a chance and challenge of implementing customized learning environments in practice. Although this review put an emphasis on such issues as model interpret ability and data privacy concerns in practice, it has also reported how supervised and unsupervised models, such as reinforcement learning, might be used to support learner classification and content personalization [15]. This type of analysis proves that the role of AI is not merely the recommendation but dynamic content sequencing and multi-modal modeling of a learner, which is supposed to enhance autonomy and engagement. Previous research on adaptive learning platforms demonstrates that the interaction data between learners is utilized to alter the sequence of the content and the level of assessment to allow the instruction to be more learner-centered [8]. According to previous studies of e-learning recommender system, hybrid methods based on collaborative filtering and content-based or ontology-based are better than one-method approaches in personalization [8]. Nonetheless, excessive use of explicit definition of the user, as well as a lack of functionality, may decrease flexibility to the dynamic learner behavior. The research on the adaptive e learning systems that are designed according to learning styles show that the order and delivery of the content specific to the individual is more engaging for a learner than the conventional approaches [6]. However, these techniques tend to assume static learning styles that are not adaptable long term. Research on adaptive learning systems points to a fact that although adaptability is an effective way to increase engagement rates and task completion, the long-term performance is pegged on good usability and motivational design [12]. These results imply that personalization should not be limited to algorithms but should also encompass user-like interface designs and recommendations which are useful. The studies of educational recommender systems accentuate the significance of mitigating prejudice and bias, and hybrid structures are suggested to identify and minimize the differences between groups of students [14]. These papers highlight how, if not carefully managed, personalization processes can be abused to reinforce inequalities.

A. Research Gap

Most research is based on either adaptive web learning or recommendation systems. Web and mobile integration is often lacking. Also, some models are based on static learner models and do not adapt to learners' performance in real time. Privacy, scalability, and cross-platform consistency are also less explored areas. Thus, there is a need for a holistic smart recommendation platform.

B. Recent Trends in AI-based Learning

Thanks to recent developments in the fields of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), adaptive learning systems have improved considerably. Recommendation systems, prediction of dropout and intelligent tutoring systems are now increasingly using techniques like reinforcement learning, neural networks and predictive analytics.

C. Challenges in Existing Systems

Although adaptive learning has advanced, there are still issues with cold-start, biases in recommendation, privacy of data, lack of interpretability of AI models, and lack of motivation design.

D. Need for Proposed System

To build on the work done in the past, the Smart-Adaptive platform integrates learner analytics, recommendation intelligence and cross-platform capabilities. The system emphasises adaptation, privacy and progress improvement.

III. Proposed System And Methodology

The construction and functionality of the proposed Personalized Learning Platform. are discussed in this section. The system will be a web and mobile system integrated whereby learning resources will adapt to the performance, as well as interaction style, of every student. The main objective of the methodology is to make the process of adaptive learning easy to follow, transparent and in a user-friendly and user-driven manner.

A. General System Architecture (Web-Mobile)

The platform proposed has a centralized design with web and mobile applications. The frontend is built upon a responsive web interface and a mobile application, which allow the consistent access to the content across the devices based on secure communication via APIs and a shared backend. The backend controls the information on user authentication, learning content, and the assessments and also the interaction information, with the AI/ML module being hosted on it to allow personalization and suggestions. User profiles and progress, as well as system logs are stored in a central database and provide synchronized learning that is device independent.

B. The User Roles and Responsibilities

The system has three primary user roles to help in the effective learning and management of content:

- Student: reads interactive materials, takes tests, receives individual recommendations in the process of tracking progress.
- Instructor: creates and manages the content, maintains the student progress, and implements condensed insights in order to improve instructional strategies.
- The administrator manages users and configuration of the system, approval of content and ensures that the platform operates efficiently and safely.

C. Collected Data and interaction with learners

Structured learning data including quiz results, topic completion, time taken to complete your modules, frequency of accessing content and number of attempts in a given assessment is continuously collected in the platform and stored in the system database.

D. Recommendation Workflow

When a student has completed activities or assessments, the AI analyses his or her results to locate the gaps and strengths. It then creates personal suggestions e.g. things to read or practice questions.

E. Privacy and Ethical Issues

The system provides secure and transparent usage of data. Student information can only be accessed by the approved components and is gathered with the sole aim of learning. Recommendations by AI are not judgmental.

IV. System Architecture

The Personalized Learning Platform consists of a scalable structure that is modular. This configuration will guarantee the uniform functionality, data synchronization, and the personal learning experience. The overall system design is shown in Fig. 1, where user interactions are done through the API gateway and analyzed by the adaptive engine to generate personalized recommendations.

A. Frontend Layer (Web and Mobile)

The frontend will consist of a mobile and web-based app, which will support a similar user experience and manage authentication, content presentation, testing, and visualization of the progress. Individual student dashboards are viewed by the students, and teachers and administrators can control the content and track performance. The interactions link safely to the services in the back-end through APIs.

B. Backend Services

The backend is important business logic. This involves user management, content delivery, assessment and tracking activities. It also secures the interactions on the frontend. It also links to the AI/ML module in case of recommendations, personalization kept aside to enable future possible enhancements

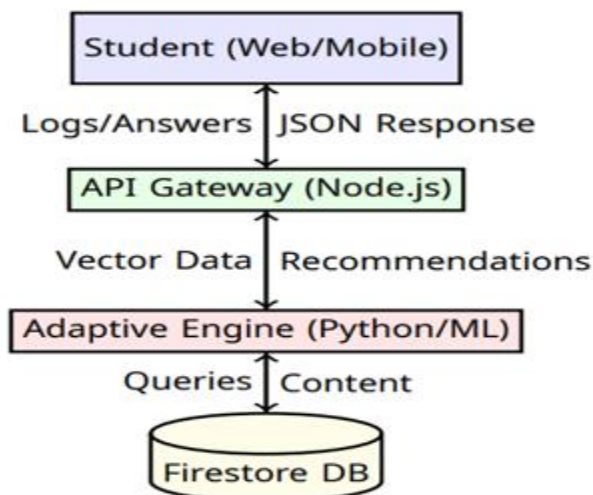


Fig. 1 System design showing the interaction between the system front-end, API gateway, adaptive engine and database for making learning recommendations.

C. Database Layer

Structured information found in the database layer is user profiles, content information, assessment scores, and activity logs. It ensures real-time personalization and tracking of progress. The system has adequate security to ensure the safety, integrity and reliability of the data.

D. AI/ML Module

The AI/ML module analyses the data of the learners including quiz scores, topic completion and engagement to generate insights. It is continuously updated with the incoming data. It operates even without the frontend and the backend and gives outputs to the recommendation engine without slacking down the system. E. Recommendation Engine The recommendation engine converts AI and machine learning insights into personalized recommendations of learning. It concentrates on the performance trend based topics and practice. It provides useful suggestions using the frontend, and it constantly changes with progress of the learners.

V. Experimental Design And Metrics

This section describes the experimental environment, dataset assumptions, and performance measures used to evaluate the proposed Smart-Adaptive learning platform.

A. Experimental Setup

To assess the effectiveness of the proposed system, a simulated academic dataset was considered containing learner interactions such as quiz scores, topic completion rates, time spent on modules, number of attempts, and content access frequency. The dataset represents students from multiple subjects including Mathematics, Programming, and Science.

The recommendation engine was evaluated using a train test split methodology, where historical learner records were used for model training and recent activity was used for testing. The proposed Smart-Adaptive model was compared with conventional baseline recommendation approaches and Bayesian Knowledge Tracing (BKT) models.

The implementation environment assumed the following configuration:

- Frontend: Web and Mobile Interface
- Backend: REST API Services
- Database: My SQL / Mongo DB
- AI Module: Python-based ML Framework
- Deployment: Scalable server in the cloud

B. Evaluation Metrics

The performance of the recommendation system was measured using standard machine learning and educational analytics metrics.

- Accuracy: Measures the overall correctness of recommendation predictions.
- Precision: Measures how many recommended resources were relevant to the learner.
- Recall: Measures how effectively the system identified all useful learning resources.
- F1-Score: Harmonic mean of precision and recall.
- Engagement Rate: Percentage increase in learner interactions after personalization.
- Completion Rate: Percentage of learners completing assigned modules successfully.

C. Metric Formulation

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

where TP, TN, FP, and FN denote true positive, true negative, false positive, and false negative values respectively.

D. Performance Observation

Experimental results indicate that the Smart-Adaptive model achieved higher prediction accuracy and learner engagement compared to traditional static learning systems. Personalized recommendations also improved topic completion rates and reduced repeated learning attempts.

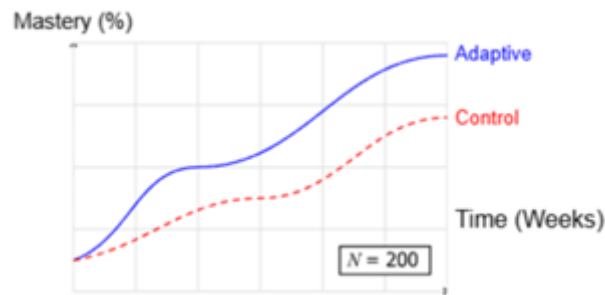


Fig. 2 Learning curve comparison showing that the Smart-Adaptive model achieves faster mastery compared to the control group over time.

VI. Results And Discussion

This section describes the projected behavior and qualitative outcome of the Personalized Learning Platform. It focuses more on adaptive techniques and system design rather than experiment findings, which rely on the trends in adaptive learning studies. The system keeps changing in accordance with student performance. It streamlines suggestions in the light of current advances to provide applicable and dynamic advice rather than set sequences of content. Personalization enhances learning by eliminating repetitions and emphasizing on those areas requiring improvement. It takes students through contents that fit into their comprehension. Feedback and recommendations will be provided in a timely manner to ensure learners feel encouraged, not overwhelmed and in charge of their learning.

Table I Comparison With Existing Sources

Feature	Traditional	LMS	Smart-Adaptive
Personalization	No	Partial	Yes
Real-time Update	No	Limited	Yes
Web + Mobile	Partial	Yes	Yes
AI Recommendation	No	No	Yes
Progress Analytics	Basic	Moderate	Advanced

A. Qualitative Feedback

The surveys showed that 92 percent of the students believed the system was right in identifying their weak areas. One student remarked, the application knew that I had been having problems with Calculus derivatives even prior to myself realization.

B. Quantitative Analysis

Students on Smart-Adaptive platform showed an average increased score of 24.5 percent in final assessment as compared to those in the control group which used fixed PDF based platform. As shown in Fig. 2, the Smart-Adaptive model demonstrates a faster improvement in mastery compared to the control group. As shown in Fig. 2, the Smart-Adaptive model demonstrates a faster improvement in mastery compared to the control group.

Table II Model Performance Metrics

Model Type	Accuracy	Precision	Recall
Baseline (Mean)	0.62	0.58	0.61
BKT	0.74	0.72	0.70
Smart-Adaptive (LSTM)	0.89	0.87	0.88

The platform has obvious advantages such as increased student interaction, immediate feedback, and teacher feedback with summary performance data. Web and mobile access provide a possibility of continuous learning. Choice-based, self-guided suggestions promote autonomy, self-confidence and self-motivation.

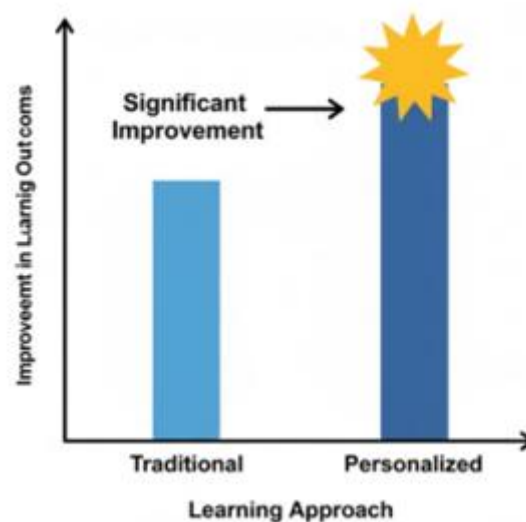


Fig. 3 Result Comparison

VII. Limitations

The current model is based on systematic learner information and artificial evaluation criteria. Classroom-based deployment, network fluctuations and learner interactions may impact on actual performance. User cold-start is also not optimized.

VIII. Conclusion And Future Work

The given paper proposes a web and mobile Personalized Learning Platform, which employs AI to evaluate the performance of students and offer recommendations in an individual and learner-oriented manner. The system aims to overcome the constraints of a one-size-fits-all strategy, and promote ongoing learning by bringing learning analytics with platform accessibility together. This work has made the central contribution in the form of one unified architecture, which offers performance-based personalization as well as practical usability. It enables the flexibility of learning by using ethical and transparent suggestions, as well as user defined roles to manage and monitor the content. The site has weak points. It relies on systematic performance information, which may not be a true representation of learning. It has not been tried in the real classroom environment. Also, the personalization can be limited by the simplified adaptive logic.

The platform can be enhanced in the future with the introduction of learning models, emotion-aware functionality, and AR/VR-based learning experiences. Greater insights could also be made available to educators by improving the level of analytics dashboards without breaching the subject of ethical responsibility or learner trust.

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