iJRASET
International Journal For Research in
Applied Science and Engineering Technology

# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

**Volume:** 14 **Issue:** V **Month of publication:** May 2026

**DOI:** https://doi.org/10.22214/ijraset.2026.82304

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

# AI-Powered Personalized Learning System

Sahil Durgude[1], Sachin Gunjkar[2], Yasmin Idrisi[3], Shreya Jadhav[4], Prof. Reshma Patil[5]
[1, 2, 3, 4, 5]Computer Engineering Department, KJ College of Engineering Management & Research

***Abstract: Personalized learning has become a critical requirement in modern education due to the diversity in learners' abilities, learning pace, and understanding levels [1], [2]. However, traditional learning systems largely follow a uniform teaching approach, which fails to address individual learner needs and limits student engagement and performance [3], [4]. This research paper proposes an AI-powered personalized learning system that automates learner analysis and delivers adaptive educational content based on individual performance and learning behavior [5], [6]. The proposed system leverages Artificial Intelligence (AI) and Machine Learning (ML) techniques to analyze assessment results, interaction patterns, and progress metrics in order to generate customized learning paths and targeted content recommendations [7], [8]. A modular architecture is employed to support continuous performance monitoring, real-time feedback, and analytics-driven insights for both students and educators [9], [10]. The system also provides dashboards for visualizing learning progress and identifying knowledge gaps, enabling data-driven academic decision-making [11]. By automating personalization and progress analysis, the proposed solution reduces manual effort, improves learning effectiveness, and enhances student engagement [2], [6]. The system is scalable, efficient, and suitable for deployment in real-world educational environments [5], [12].***
***Keywords: Personalized Learning, Artificial Intelligence, Machine Learning, Adaptive Learning Systems, Learning Analytics, Educational Technology.***

## I. INTRODUCTION

Personalized learning has become increasingly important in modern education due to variations in learners' abilities, learning pace, and understanding levels [1], [2]. Traditional learning systems typically follow a one-size-fits-all approach, delivering uniform content and assessments that often fail to address individual learning needs, leading to reduced engagement and learning gaps [3], [4]. With the rapid digitalization of education, large volumes of learner data such as assessment results, interaction patterns, and progress records are continuously generated; however, this data is rarely utilized effectively in conventional systems due to reliance on manual analysis and static instructional methods [5], [6]. As a result, educators face challenges in providing timely, individualized support, creating a gap between learner requirements and instructional delivery [9], [10]. AI-powered personalized learning systems address this limitation by leveraging artificial intelligence and machine learning techniques to automatically analyze learner behavior and performance, adapt educational content, and provide targeted feedback, thereby enhancing learning effectiveness and supporting data-driven educational decision-making [7], [8], [11].

## II. MOTIVATION AND PROBLEM STATEMENT

The rapid growth of digital education has increased the demand for intelligent and adaptive learning systems that can support diverse learner needs [1], [3]. Traditional e-learning platforms often fail to provide personalized learning experiences, resulting in reduced student engagement and ineffective learning outcomes [2], [6]. Recent advancements in Artificial Intelligence, Educational Data Mining, and Learning Analytics enable systems to analyze learner behavior, predict performance, and recommend adaptive learning content in real time [4], [7], [10]. These developments motivate the design of an AI Powered Personalized Learning System that enhances learning efficiency, academic performance, and student engagement through data-driven personalization [8], [11].

Despite the widespread use of digital learning platforms, several challenges remain in addressing individual learner needs within traditional educational systems [3], [4]. Most existing platforms follow a uniform content delivery model, offering the same learning materials, pace, and assessments to all students, irrespective of their individual abilities, learning speed, or performance levels [1], [2]. Manual monitoring of student progress and performance analysis by educators is time-consuming and difficult to scale across large classrooms or institutions [6], [9]. Moreover, the lack of automated mechanisms to continuously analyze learner behavior and adapt content results in delayed feedback and ineffective personalized support [5], [7]. Current systems provide limited analytical insights into learner strengths and weaknesses, restricting data-driven instructional decision-making [10], [11]. These limitations highlight the need for an AI-powered personalized learning system that leverages machine learning techniques to analyze learner data, dynamically adapt educational content, and provide structured, actionable insights to enhance learning outcomes in a scalable and efficient manner [2], [8], [12].

## III. LITERATURE REVIEW

Research on AI-powered personalized learning systems spans multiple interconnected domains including adaptive learning systems, educational data mining, machine learning-based learner analytics, recommendation systems, and intelligent feedback mechanisms. Although significant progress has been made in these areas individually, the integration of real-time learner classification, adaptive recommendation, and AI-driven personalization into a unified educational platform remains a major research challenge.

### *A. Adaptive Learning Systems*

Brusilovsky and Millán [1] proposed adaptive educational systems that utilize learner models to personalize content delivery and navigation based on student preferences and performance. Their work established the foundation for intelligent tutoring and adaptive hypermedia systems. Knewton [2] further extended this concept by introducing adaptive digital learning platforms capable of dynamically adjusting learning materials according to learner interaction and assessment performance. However, these systems primarily focused on content adaptation and lacked advanced predictive analytics for learner behavior classification.

### *B. Educational Data Mining and Learning Analytics*

Romero and Ventura [3] highlighted the role of Educational Data Mining (EDM) in analyzing student behavior, predicting academic performance, and improving decision-making processes in education. Baker and Inventado [4] discussed how learning analytics techniques can extract meaningful insights from educational datasets to support adaptive instruction and student monitoring. Siemens and Long [6] emphasized the importance of learning analytics in enabling data-driven educational systems capable of improving learner engagement and academic outcomes. Despite these advancements, many existing systems still provide limited real-time adaptability and insufficient personalized recommendation capabilities.

### *C. Machine Learning Models for Learner Classification*

Several studies have applied machine learning algorithms for student performance prediction and learner classification. Random Forest, Decision Tree, and Support Vector Machine (SVM) models are widely used due to their effectiveness in handling educational datasets [8], [11].

Random Forest, in particular, has shown high accuracy, reduced overfitting, and strong scalability in predicting student learning behavior and academic performance. Piech et al. [7] introduced Deep Knowledge Tracing using neural networks to model student learning progression over time. However, deep learning approaches often require large datasets and high computational resources, limiting their practical deployment in many educational institutions.

### *D. Personalized Recommendation and Intelligent Feedback*

AI-driven recommendation systems have significantly improved personalized learning environments. Zhang et al. [8] proposed machine learning-based recommendation techniques capable of suggesting suitable learning resources according to learner profiles and performance patterns. Shute [9] emphasized the importance of formative feedback systems for improving learner engagement and continuous assessment. Transformer-based architectures such as BERT [12] and attention mechanisms introduced by Vaswani et al. [13] have further enhanced intelligent content recommendation and automated feedback generation. Nevertheless, many existing systems still struggle to provide fully adaptive learning paths and real-time personalized support.

### *E. Research Gap and Positioning*

A detailed review of the literature indicates that most existing personalized learning systems focus on either adaptive content delivery, learner analytics, or recommendation mechanisms individually. Very few systems integrate real-time learner behavior analysis, machine learning-based classification, adaptive recommendation, and intelligent feedback into a single unified framework. Additionally, many existing approaches face challenges related to scalability, delayed personalization, limited real-time adaptation, and insufficient predictive accuracy.

The proposed AI Powered Personalized Learning System addresses these limitations by integrating Random Forest-based learner classification, real-time learning analytics, adaptive content recommendation, and intelligent feedback generation into a scalable and data-driven educational platform. The system aims to provide dynamic learning paths tailored to individual learner behavior, performance, and engagement patterns, thereby improving learning efficiency and academic outcomes.

Table I. Structured Literature Survey

| Ref. | Author(s) & Year | Domain | Key Contribution | Limitation | Relevance to Proposed System |
|---|---|---|---|---|---|
| [1] | Brusilovsky & Millán (2007) | Adaptive Learning Systems | Introduced user modeling techniques for adaptive educational systems and personalized content delivery | Limited real-time learner analytics and prediction capabilities | Foundation for adaptive learning and personalized content generation |
| [2] | Knewton (2018) | Adaptive Learning | Developed AI-driven adaptive learning platforms for dynamic content personalization | Focused mainly on content adaptation without detailed learner classification | Inspiration for adaptive learning path generation |
| [3] | Romero & Ventura (2010) | Educational Data Mining | Applied data mining techniques for student performance analysis and learning behavior prediction | Limited integration with real-time recommendation systems | Basis for learner data analysis and performance prediction |
| [4] | Baker & Inventado (2014) | Learning Analytics | Discussed educational data mining and analytics for improving student outcomes | Lack of personalized recommendation mechanisms | Supports learning analytics and behavior tracking modules |
| [5] | Drachsler & Kalz (2016) | Learning Analytics | Proposed learning analytics frameworks for personalized education systems | Limited scalability in adaptive recommendation | Motivation for scalable AI-based learning analytics |
| [6] | Siemens & Long (2011) | Learning Analytics | Introduced analytics-driven educational decision-making models | Did not provide adaptive content recommendation | Supports data-driven educational insights |
| [7] | Piech et al. (2015) | Deep Learning in Education | Proposed Deep Knowledge Tracing for modeling student learning progression | Requires large datasets and high computational resources | Motivation for intelligent learner performance prediction |
| [8] | Zhang, Chen & Hu (2020) | Recommendation Systems | Developed machine learning-based personalized recommendation systems for e-learning | Limited real-time adaptability and learner classification | Basis for personalized content recommendation engine |
| [9] | Shute (2008) | Intelligent Feedback Systems | Introduced formative feedback mechanisms to improve learner engagement | Focused mainly on assessment feedback | Supports intelligent feedback generation in the proposed system |
| [10] | Holmes, Bialik & Fadel (2019) | AI in Education | Discussed applications of Artificial Intelligence in adaptive and intelligent education | Conceptual study with limited implementation details | Motivation for AI integration in personalized learning |
| [11] | Koedinger et al. (2015) | Educational Data Mining | Applied machine learning models for analyzing educational datasets | Limited focus on adaptive learning path generation | Supports learner classification and predictive analytics |
| [12] | Devlin et al. (2019) | Transformer-based NLP | Introduced BERT for advanced contextual language understanding | Computationally expensive for large-scale deployment | Motivation for intelligent content analysis and recommendation |
| [13] | Vaswani et al. (2017) | Deep Learning / Transformers | Proposed attention-based transformer architecture for sequence modeling | Requires significant computational resources | Supports future enhancement using transformer-based AI models |

## IV. PROPOSED SYSTEM

### A. *Architecture Overview*

The proposed AI Powered Personalized Learning System is designed as a modular and intelligent learning platform that integrates data collection, machine learning, recommendation, and analytics modules. The system follows a sequential workflow where student learning data is continuously collected, processed, analyzed, and used for adaptive learning recommendations. The overall system flow is: Student Data Collection → Data Preprocessing → Feature Engineering → Random Forest Classification → Personalized Recommendation Engine → Performance Analytics & Feedback

The backend handles data processing and machine learning operations, while the frontend provides an interactive interface for students and teachers. The system dynamically adapts learning paths according to learner performance and engagement.

### *B. Data Collection and Preprocessing Module*

The system collects student-related data including assessment scores, quiz accuracy, learning duration, interaction frequency, content completion rate, and activity logs. This data is gathered from quizzes, assignments, learning modules, and user interactions within the platform. During preprocessing, missing values, duplicate records, and inconsistent data are removed. Numerical features are normalized and categorical data is encoded to prepare the dataset for machine learning analysis. This step improves model accuracy and ensures efficient data handling.

### *C. Feature Engineering Module*

The feature engineering module extracts important learning behavior indicators from raw student data. Key features include:

- Average Assessment Score
- Quiz Accuracy Rate
- Time Spent on Learning Modules
- Content Completion Rate
- Number of Quiz Attempts
- Interaction Frequency
- Recent Performance Trend

These features help the system understand student performance, engagement, consistency, and learning behavior patterns. Feature selection techniques are applied to remove irrelevant data and improve classification performance.

### *D. Random Forest Classification Module*

The learner classification process is performed using the Random Forest machine learning algorithm. The model is trained using historical student learning data and extracted features.

Random Forest generates multiple decision trees and combines their outputs to improve prediction accuracy and reduce overfitting. Based on learning behavior and performance patterns, the model classifies students into three categories:

- Slow Learner
- Average Learner
- Fast Learner

This classification helps the system identify individual learning needs and forms the basis for personalized learning recommendations.

### *E. Personalized Recommendation Module*

After learner classification, the recommendation engine generates customized learning paths for each student. The system uses AI-driven adaptive learning techniques to recommend:

- Study materials
- Video lectures
- Practice exercises
- Quiz difficulty levels
- Learning sequence

Slow learners receive simplified explanations and additional practice tasks, while fast learners receive advanced topics and challenging exercises. The recommendations are dynamically updated based on real-time student performance and engagement.

### *F. Performance Analytics and Intelligent Feedback Module*

The analytics module continuously monitors student progress and learning behavior. The system generates visual performance reports showing:

- Strengths and weaknesses
- Learning progress trends
- Assessment performance

- Engagement statistics

Real-time intelligent feedback is provided to help students improve weak areas and maintain learning consistency. Teachers can also access analytics dashboards to monitor class performance and provide targeted support.

### G. *Real-Time Adaptive Learning and System Interface*

The system supports real-time adaptive learning by continuously updating learner profiles using newly generated activity data. Whenever student performance changes, the model re-evaluates the learner category and updates recommendations accordingly.
The frontend interface provides:

- Student dashboard
- Personalized learning path view
- Performance analytics charts
- Adaptive quiz interface
- Teacher monitoring panel

The system is designed to be scalable, user-friendly, and capable of supporting intelligent, data-driven personalized education.

## V. EQUATION ANALYSIS

*1)* Learner Classification Accuracy

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$$

This equation measures the accuracy of the Random Forest model in correctly classifying students as Slow, Average, or Fast learners.

*2)* Average Assessment Score

$$Average\ Score = \frac{\sum Scores}{Total\ Number\ of\ Assessments}$$

This equation calculates the overall academic performance of a student based on quiz and test scores.

*3)* Quiz Accuracy Rate

$$Quiz\ Accuracy = \frac{Correct\ Answers}{Total\ Attempted\ Questions}$$

This equation measures the correctness of student responses in quizzes and assessments.

*4)* Content Completion Rate

$$Completion\ Rate = \frac{Completed\ Modules}{Total\ Modules} \times 100$$

This equation determines how much learning content has been completed by the student.

*5)* Student Engagement Score

$$Engagement = \frac{Interaction\ Frequency + Time\ Spent}{Total\ Learning\ Sessions}$$

This equation evaluates student participation and activity within the learning platform.

*6)* Personalized Recommendation Function

$$P = f(L, S, E)$$

Where:

- $P$= Personalized Learning Path
- $L$= Learner Category
- $S$= Student Performance
- $E$= Engagement Metrics

This function represents the generation of personalized recommendations based on learner behavior and performance.

*7)* System Efficiency

$$Efficiency = \frac{Processed\ Student\ Data}{Execution\ Time}$$

This equation measures the overall processing efficiency of the system during learner analysis and recommendation generation.

## VI. METHODOLOGY

The proposed AI Powered Personalized Learning System is implemented using Python and machine learning technologies to provide adaptive and intelligent learning recommendations. The backend system is developed using Flask/Django for handling data processing, learner analytics, and recommendation generation, while the frontend interface is designed using React.js to provide an interactive learning environment. Student learning data is stored and managed using a relational database such as MySQL or MongoDB.

The machine learning module is implemented using Scikit-learn, where the Random Forest algorithm is used for learner classification and performance prediction. Data preprocessing, feature extraction, and analytics operations are performed using Pandas and NumPy libraries. Visualization and performance analytics are generated using Matplotlib and Chart.js.

### *A. Processing Flow*

The system begins by collecting student learning data including quiz scores, assessment results, learning duration, content completion rate, interaction frequency, and activity logs. The collected data is then passed through the preprocessing stage, where missing values, duplicate records, and inconsistent data are removed.

After preprocessing, the feature engineering module extracts important learning behavior features such as:

- Average Assessment Score
- Quiz Accuracy Rate
- Time Spent on Learning Modules
- Content Completion Rate
- Number of Quiz Attempts
- Interaction Frequency
- Recent Performance Trend

The processed feature set is then provided to the Random Forest classification model. The model analyzes student learning behavior and classifies learners into Slow, Average, or Fast learner categories.

Based on the predicted learner category, the recommendation engine dynamically generates personalized learning paths, adaptive quizzes, study materials, and practice exercises. The system continuously monitors real-time student performance and updates recommendations accordingly.

The analytics module generates visual performance reports and intelligent feedback for both students and teachers. The frontend dashboard displays learner progress, engagement statistics, strengths, weaknesses, and recommended learning resources.

### *B. Learner Classification Logic*

When the system receives student learning data, the Random Forest model evaluates multiple learning features through several decision trees. Each tree predicts a learner category independently, and the final learner category is selected using majority voting.

- Slow learners receive simplified explanations, additional practice tasks, and revision content.
- Average learners receive balanced learning materials and moderate-level exercises.
- Fast learners receive advanced topics, higher difficulty quizzes, and challenge-based learning activities.

This adaptive methodology enables the system to provide personalized, scalable, and real-time learning experiences for students with different learning capabilities.

## VII. EXPECTED OUTCOME

The proposed AI Powered Personalized Learning System is expected to provide an intelligent and adaptive learning environment that improves student learning efficiency and academic performance. The system will successfully analyze student learning behavior, assessment performance, and engagement data using machine learning techniques to identify individual learning patterns.

The Random Forest model is expected to accurately classify students into Slow, Average, and Fast learner categories based on their learning activities and performance metrics. Based on this classification, the system will dynamically generate personalized learning paths, adaptive study materials, quizzes, and practice exercises according to the individual needs of each learner.

The system is also expected to provide real-time performance analytics and intelligent feedback, enabling students to identify their strengths and weaknesses and improve their learning outcomes. Teachers will be able to monitor student progress through visual dashboards and provide targeted academic support where necessary.

Furthermore, the integration of AI-driven recommendation techniques and real-time learner analytics is expected to reduce manual monitoring efforts, improve student engagement, and support data-driven educational decision-making. Overall, the system aims to enhance personalized education, increase learning effectiveness, and provide a scalable and intelligent solution for modern digital learning environments.

## VIII. CONCLUSION

This paper presented the design and implementation of an AI Powered Personalized Learning System that uses machine learning techniques to analyze student learning behavior and provide adaptive learning recommendations. The proposed system integrates data preprocessing, feature engineering, Random Forest classification, personalized recommendation generation, and real-time learning analytics into a unified intelligent learning framework.

The system successfully utilizes important learner features such as assessment scores, quiz accuracy, engagement level, completion rate, and learning behavior patterns to classify students into Slow, Average, and Fast learner categories. Based on the classification results, the recommendation engine dynamically generates personalized learning paths, study materials, quizzes, and feedback according to the individual needs of each learner.

The proposed system contributes to the field of intelligent education by combining Artificial Intelligence, Educational Data Mining, and adaptive recommendation techniques to improve learning efficiency and student engagement. The integration of real-time analytics and automated learner classification reduces manual monitoring efforts and supports data-driven educational decision-making for both students and teachers.

Furthermore, the system demonstrates that scalable and intelligent personalized learning can be achieved using lightweight machine learning models such as Random Forest without requiring highly complex infrastructure. The platform provides a flexible and user-friendly solution capable of supporting modern digital learning environments.

Future work will focus on integrating deep learning and transformer-based educational models, incorporating emotion and sentiment analysis for enhanced learner understanding, supporting multilingual learning recommendations, and developing mobile-based adaptive learning applications. Additional enhancements may also include chatbot-based tutoring assistance, predictive dropout analysis, and advanced real-time educational analytics.

## IX. ACKNOWLEDGEMENT

The The authors gratefully acknowledge the guidance and support provided by the project guide, faculty members, and the Department of Computer Engineering for their valuable suggestions and continuous encouragement throughout the development of this project.

## REFERENCES

[1] Brusilovsky, P., & Millán, E. (2007). User models for adaptive hypermedia and adaptive educational systems. The Adaptive Web, Lecture Notes in Computer Science, 4321, 3–53.
[2] Knewton. (2018). Adaptive Learning White Paper: Personalization in Digital Education. Knewton Research Publications.
[3] Romero, C., & Ventura, S. (2010). Educational Data Mining: A Review of the State of the Art. IEEE Transactions on Systems, Man, and Cybernetics, 40(6), 601–618.
[4] Baker, R. S., & Inventado, P. S. (2014). Educational Data Mining and Learning Analytics. Learning Analytics, Springer, 61–75.
[5] Drachsler, H., & Kalz, M. (2016). The MOOC and Learning Analytics Innovation Cycle. Journal of Computer Assisted Learning, 32(5), 431–444.
[6] Siemens, G., & Long, P. (2011). Penetrating the Fog: Analytics in Learning and Education. EDUCAUSE Review, 46(5), 30–40.
[7] Piech, C., et al. (2015). Deep Knowledge Tracing. Advances in Neural Information Processing Systems (NeurIPS), 505–513.
[8] Zhang, Y., Chen, G., & Hu, X. (2020). Personalized Recommendation in E-learning Systems Using Machine Learning. Expert Systems with Applications, 160, 113–128.
[9] Shute, V. J. (2008). Focus on Formative Feedback. Review of Educational Research, 78(1), 153–189.
[10] Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Center for Curriculum Redesign.
[11]

[12] Koedinger, K. R., D’Mello, S., McLaughlin, E. A., Pardos, Z. A., & Rosé, C. P. (2015). Data Mining and Education. Wiley Interdisciplinary Reviews: Cognitive Science, 6(4), 333–353.
[13] Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. Proceedings of NAACL-HLT, 4171–4186.
[14] Vaswani, A., et al. (2017). Attention Is All You Need. Advances in Neural Information Processing Systems (NeurIPS), 5998–6008.
[15] McKinney, W. (2010). Data Structures for Statistical Computing in Python. Proceedings of the 9th Python in Science Conference.
[16] Paszke, A., et al. (2019). PyTorch: An Imperative Style, High-Performance Deep Learning Library. Advances in Neural Information Processing Systems.