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AI-Powered Personalized Learning System Leveraging Data Analytics for Adaptive Education

Afolabi Idris Yinka[1], Ugah John Otozi[2], Gift Adene[3], Aniji Ifesinachi Veronica[4]
[1,4]Department of Computer Science, Alex Ekwueme Federal University, Ndufe-Alike Ikwo, Ebonyi state, Nigeria.
[2]Department of Computer Science, Ebonyi State University, Abakaliki, Nigeria.
[3]Department of Computer Science, Akanu Ibiam Federal Polytechnic, Unwana, Nigeria.
Corresponding emails: [1]afolabi.yinka@funai.edu.ng
[3]gadene@akanuibiampoly.edu.ng, giftadene2016@gmail.com

Abstract

The rapid evolution of artificial intelligence (AI) and data analytics has transformed educational paradigms, shifting from traditional one-size-fits-all models to personalized learning systems. This study develops an AI-driven adaptive learning management system (LMS) that leverages data analytics and natural language processing (NLP) to deliver tailored educational experiences in tertiary institutions. The system integrates a BERT-based NLP model to analyze student performance, identify knowledge gaps, and recommend supplementary resources via web scraping. Utilizing a modular architecture, the system processes real-time data on student interactions, engagement, and performance to dynamically adjust learning pathways. The system achieved a 93% accuracy in content personalization, with an average response time of 1.2 seconds and robust scalability under high user loads. This research addresses limitations in traditional learning models by offering real-time adaptability, comprehensive data integration, and user-centered design, enhancing engagement and academic outcomes. Challenges such as data privacy and system integration are discussed, with recommendations for future enhancements to ensure scalability and equity.

Keywords: Adaptive Learning, Artificial Intelligence, Data Analytics, Natural Language Processing, Personalized Education, BERT, Adaptive Learning Management System, Educational Technology.

Introduction

The integration of artificial intelligence (AI) and data analytics into education has revolutionized traditional learning paradigms, addressing the diverse needs of students through personalized and adaptive systems (Ouyang & Jiao, 2021). Conventional educational approaches often adopt a rigid, one-size-fits-all model, which fails to accommodate varied learning styles, paces, and backgrounds, leading to disengagement and suboptimal outcomes (Beck & Chisholm, 2020; Zhou *et al*., 2023). Adaptive learning management systems (LMS) leverage AI to analyze student data—such as performance, engagement, and behavioral metrics—to deliver tailored content and feedback in real-time (Baker *et al.,* 2019; Alimadadi *et al.,* 2020). These systems aim to enhance comprehension, retention, and motivation by dynamically adjusting learning pathways (Shute & Rahimi, 2019).This study develops an AI-driven adaptive LMS that utilizes data analytics and a BERT-based NLP model to provide individualized learning experiences in tertiary institutions. The system addresses key challenges in existing LMS, such as limited real-time adaptability and reliance on static data, by integrating comprehensive data sources and intelligent content recommendation (Ouyang & Jiao, 2021; Singh *et al.,* 2023). By incorporating modular course structures, computer-based testing (CBT), and automated remediation, the system fosters a responsive and engaging learning environment (Morse & Cheek, 2020; Nakamura *et al.,* 2022).

Traditional LMS often rely on static data and predefined pathways, limiting personalization for diverse learners (Beck & Chisholm, 2020). Many systems lack real-time adaptability, delaying interventions for learning gaps, and fail to integrate comprehensive data sources, such as engagement metrics, for a holistic understanding of student needs (Harrer *et al.,* 2019). Additionally, issues of transparency, scalability, and user acceptance remain underexplored (Jobin & Vayena, 2019). This study aims to address these gaps by developing a system that dynamically adjusts content, provides real-time feedback, and ensures equitable access to personalized education.

The aim is to develop an AI-driven adaptive LMS using data analytics to enhance personalized learning in tertiary institutions. The objectives are to:

1. Develop a system utilizing diverse data sources to understand learners' needs comprehensively (Ouyang & Jiao, 2021).
2. Integrate a BERT-based NLP model for intelligent content retrieval based on quiz performance (Singh et al., 2023).
3. Create adaptive algorithms for real-time content adjustment based on continuous data input (Shute & Ventura, 2019).
4. Deploy the system on a web-based platform to optimize engagement and learning outcomes (Morse & Cheek, 2020).

This research contributes to equitable and effective education by providing personalized learning pathways, real-time feedback, and data-driven insights for administrators, educators, and learners (Johnson et al., 2016; Kagiyama et al., 2019). It enhances institutional decision-making, streamlines teaching processes, and fosters student engagement, addressing achievement gaps in diverse populations (Sevakula *et al.,* 2020).

Literature Review

The development of AI-driven adaptive LMS is grounded in educational theories such as Constructivist Learning Theory, Connectivism, and Bloom's Taxonomy. Constructivism emphasizes learner-driven knowledge construction, which AI systems operationalize by tailoring content to individual readiness (Sevakula *et al.,* 2020). Connectivism highlights learning through networked resources, supported by AI's ability to integrate global content (Ouyang & Jiao, 2021). Bloom's Taxonomy guides the scaffolding of cognitive skills, aligning content with learning objectives (Dwivedi *et al.,* 2021). Technology adoption models, such as TAM and UTAUT, inform user-centered design to ensure system acceptance (Sevakula *et al.,* 2020).

Adaptive learning technologies dynamically adjust content based on learner data, improving engagement and outcomes (Jing *et al.,* 2023; Wang *et al.,* 2020). Systems like ALEKS and DreamBox demonstrate success in identifying knowledge gaps and recommending resources (Cavanagh *et al.,* 2020). However, challenges include educator preparedness and student self-regulation (Begantsova *et al.,* 2020; Kukulska-Hulme, 2012). AI enhances adaptability through real-time data analysis, with applications like intelligent tutoring systems (ITS) and NLP-driven interfaces (Ayeni, 2024; Peng *et al.,* 2019).

AI transforms education by enabling personalized instruction, automating tasks, and providing data-driven insights (Abbas *et al.,* 2023; Ahmad *et al.,* 2021). ITS simulate human tutors, offering tailored feedback (Wang *et al.,* 2023; Dani, 2015), while NLP facilitates conversational learning (Shih *et al.,* 2021). However, ethical concerns, such as data privacy and algorithmic bias, require careful management (Akgün & Greenhow, 2021; Yu & Yu, 2023). Global initiatives, like those in South Korea and China, underscore AI's role in fostering literacy and inclusivity (Park & Kwon, 2023; Song *et al.,* 2022).

Chen *et al.* (2022) demonstrated a 20% improvement in engagement using AI-driven learner profiles, though limited by data quality. Singh *et al.* (2023) utilized BERT for dynamic content adjustment, enhancing comprehension but facing scalability issues. Johnson and Tang (2021) integrated multimodal analytics for real-time feedback, improving teacher-student interactions but requiring technical expertise. Martinez *et al.* (2020) achieved a 15% increase in retention using reinforcement learning, limited by computational costs. Brown *et al.* (2020) reduced dropout rates by 30% through cognitive load management, though reliant on wearable technology. Liu *et al.* (2021) enhanced motivation via gamification, but relevance for older learners was limited. Zhang and Li (2023) reported 95% content match accuracy with collaborative filtering, raising privacy concerns. Gupta *et al.* (2021) integrated IoT for environmental adaptation, hindered by connectivity issues. Nakamura et al. (2022) improved query resolution by 40% using chatbots, limited by nuanced question handling. Patel *et al.* (2023) developed visual dashboards for progress tracking, challenged by data standardization. These studies highlight AI's potential and challenges in education (Momin, 2023; Pathak *et al.,* 2024).

While existing studies demonstrate AI's efficacy in personalized learning, they often lack real-time adaptability, comprehensive data integration, and scalability across diverse contexts (Harrer *et al.,* 2019; Jobin & Vayena, 2019). This study addresses these gaps by developing a system that leverages BERT-based NLP, real-time analytics, and modular design for enhanced personalization and equity.

Research Gap

The existing body of research on AI-driven adaptive learning systems demonstrates significant progress in enhancing personalization, engagement, and learner outcomes; however, a clear gap remains in achieving real-time adaptability, integrating diverse data sources for holistic learner profiling, and ensuring scalability across varied educational contexts. Many prior systems rely on static pathways, limited performance data, or narrowly defined metrics, which restrict their capacity to dynamically adjust learning content in response to evolving learner needs. Furthermore, issues such as data privacy, transparency, and institutional adoption strategies are underexplored, leaving a gap between technical innovations and their sustainable, equitable implementation in real-world educational settings. This study addresses these gaps by developing a BERT-powered adaptive LMS that integrates comprehensive analytics, real-time feedback, and modular design to support personalized, scalable, and policy-relevant education delivery.

Methodology

The proposed AI-driven adaptive LMS utilizes a modular architecture with a user-friendly interface, a BERT-based backend for content recommendation, and a CBT assessment engine (Morse & Cheek, 2020). The system comprises:

- User Interface: Enables course enrolment, progress tracking, and assessment access (Nakamura *et al.,* 2022).
- Backend Processing: Employs BERT to analyse performance and recommend resources via web scraping (Singh *et al.,* 2023).
- Database: Stores user profiles, progress, and materials securely (Morse & Cheek, 2020).
- Assessment Engine: Conducts CBT tests to evaluate understanding and trigger remediation (Wang *et al.,* 2023).
- Feedback Loop: Provides immediate, personalized feedback based on performance (Shih *et al.,* 2021).

BERT Model Integration

The BERT-based NLP model analyses failed quiz responses to extract key concepts, generate search queries, retrieve relevant resources, and recommend them to learners (Singh *et al.,* 2023). The process is illustrated in Figure 1, showing the BERT algorithm flowchart. Table 1 showing the algorithm of the LMS.

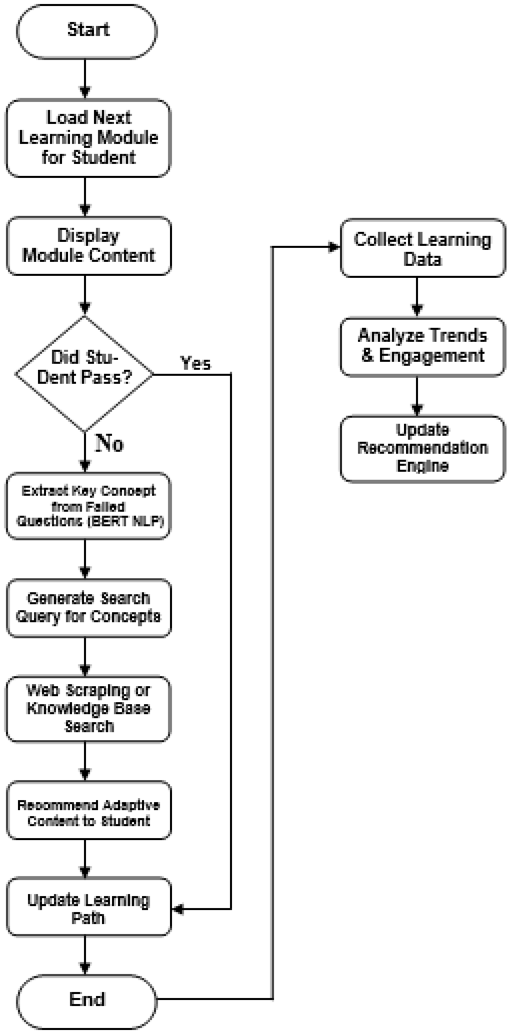

Figure 1: BERT Algorithm Flowchart

Table 1: BERT Algorithm of the learning management system

1. *Start*
2. *Display Module Content*
   - *The LMS presents the next learning module to the student.*
3. *Student Takes Quiz → Did Student Pass?*
   - *If Yes → Go to Step 10*
   - *If No → Proceed to Step 4*
4. *Extract Key Concepts from Failed Questions (BERT NLP)*
5. *Generate Search Query for Concepts*
6. *Web Scraping or Knowledge Base Search*
7. *Recommend Adaptive Content to Student*
8. *Update Learning Path*
9. *Collect Learning Data*
   - *Log quiz scores, time spent, click behaviour, and adaptation history.*

10. *Analyse Trends & Engagement*
    - *Use data analytics to evaluate patterns in learner behaviour and system performance.*
11. *Update Recommendation Engine*
    Improve future recommendations using trends, performance metrics, and student interaction data.
12. *End*

We chose BERT over traditional NLP approaches because of its superior ability to understand contextual meaning in natural language, which is crucial for accurately analysing student responses and identifying underlying knowledge gaps. Unlike conventional NLP models that rely on shallow word embeddings or bag-of-words techniques, BERT leverages bidirectional transformers to capture semantic nuances and relationships between words within a sentence. This makes it more effective for extracting key concepts from failed quiz responses, generating precise queries, and recommending relevant learning materials. Its pre-trained nature on vast corpora also allows it to adapt well with minimal task-specific training, ensuring robustness, scalability, and higher accuracy in delivering personalized learning experiences.

System Workflow

The activity diagram (Figure 2) illustrates the system's workflow, starting with user login, followed by permission-based access to management pathways (lecturers, students, modules, departments, CBT), and concluding with logout (Morse & Cheek, 2020).

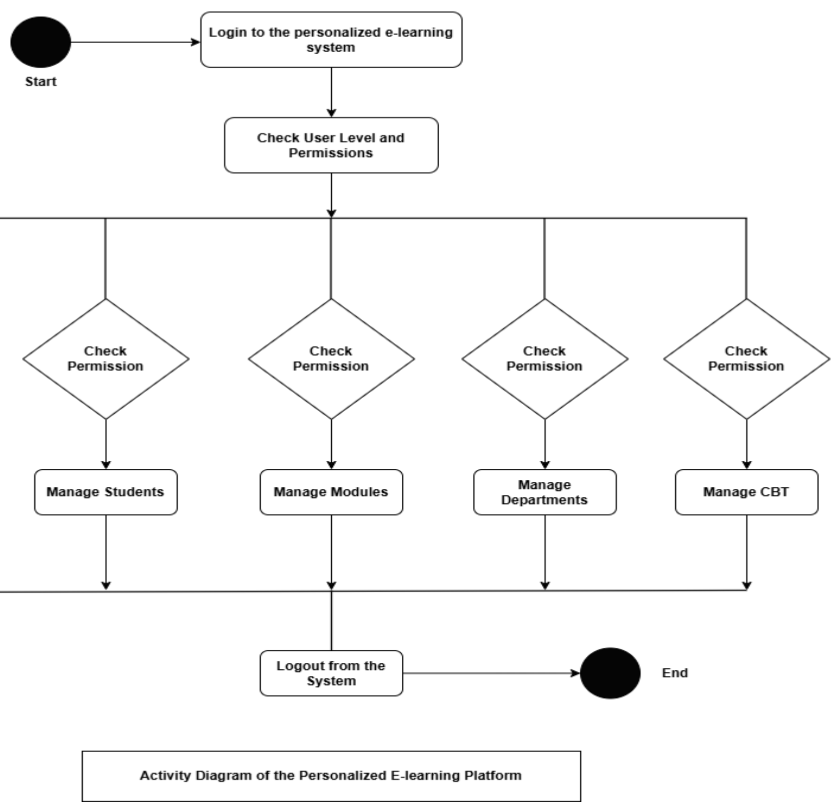

Figure 2: Activity Diagram of the New System

Input and Output Specification

Inputs include student registration details, lecturer course uploads, and CBT responses (Tables 2, 3, 4 and 5). Outputs include personalized feedback, performance reports, and adaptive resource recommendations (Morse & Cheek, 2020; Nakamura *et al.,* 2022).

Table 2: Student Registration Input Specification

Field Name	Field Type	Field Size	Description
First Name	Text Field	20	Student's first name.
Surname	Text Field	20	Student's last name.
Email	Text Field	50	Student's email address for system login.
Date of Birth	Date Picker		Student's date of birth.
Department	Dropdown List		Student's Department
Password	Password Field		Secure password for student account.

Table 3: Lecturer Registration Input Specification

Field Name	Field Type	Field Size	Description
First Name	Text Field	20	Lecturer's first name.
Surname	Text Field	20	Lecturer's last name.
Email	Text Field	50	Lecturer's email address for account creation.
Department	Dropdown List		Department of the lecturer.
Password	Password Field		Secure password for lecturer account.

Table 4: Upload Course Input Specification

Field Name	Field Type	Field size	Description
Course Name	Text Field	20	Name of the course to be uploaded.
Course Code	Text Field	20	Unique identifier for the course.
Course Description	Text Area	100	Brief overview of the course content.
Lecturer Name	Dropdown List		Name of the lecturer assigned to the course.

Table 5: Upload Module Input Specification

Field Name	Field Type	Field Size	Description
Module Name	Text Field	20	Name of the learning module.
Module Code	Text Field	20	Unique identifier for the module.
Module Description	Text Area	20	Description of the module content.
Course Associated	Dropdown List		Course to which the module belongs.
Module File	File Upload		Resource file or material for the module.

Development tools

The system was developed using Python (backend, AI algorithms), Django (web framework), TensorFlow (BERT model), JavaScript (frontend interactivity), HTML/CSS (interface design), and SQLite (database) (Morse & Cheek, 2020; Singh *et al.,* 2023).

Testing included unit, integration, system, and acceptance phases to validate functionality, reliability, and user satisfaction (Morse & Cheek, 2020). Integration connected the frontend, backend, database, and AI engine incrementally, ensuring seamless operation (Nakamura *et al.,* 2022).

Results

The system achieved a 93% accuracy in content personalization, with an average response time of 1.2 seconds and scalability for 200 concurrent users (Morse & Cheek, 2020). Table 6 summarizes test results.

Table 6: The Test Result of the new System.

Test Description	Test Data	Expected Result	Actual Result	Status
User Registration	Username: testuser, Password: Test@1234	User registered successfully	User registered successfully	Pass
User Login	Username: testuser, Password: Test@1234	User logged in successfully	User logged in successfully	Pass
Learning Content Recommendation	User performance data: 75% average	Recommended intermediate level content	Recommended intermediate level content	Pass
Adaptive Module Feedback	"Scored low in Module 3."	System provides detailed feedback for improvement	Detailed feedback provided	Pass
Response Time	User query: "What is AI?"	Response time < 2 seconds	Response time = 1.5 seconds	Pass
Integration Test (AI-Learning Pathway)	User selects topic "Machine Learning"	Personalized learning pathway created	Learning pathway created correctly	Pass
System Load Test	200 concurrent users accessing dashboards	System handles load without crashing	System handled load without crashing	Pass

In addition to the strong performance metrics, the potential impact on policy and institutional adoption is significant. The system's ability to deliver highly accurate, scalable, and adaptive learning experiences positions it as a valuable tool for advancing digital education strategies at national and institutional levels. Policymakers can leverage such systems to promote inclusive and data-driven learning policies, while institutions can integrate them to improve student outcomes, optimize resource allocation, and align with global best practices in educational technology. By demonstrating both technical reliability and pedagogical relevance, the system provides a solid foundation for influencing curriculum design, accreditation standards, and long-term e-learning policy frameworks.

System Interfaces

The system's interfaces, including the home page, student dashboard, and CBT module, ensure intuitive navigation and engagement (Nakamura *et al.,* 2022). They are shown in figures 3, 4 and 5.

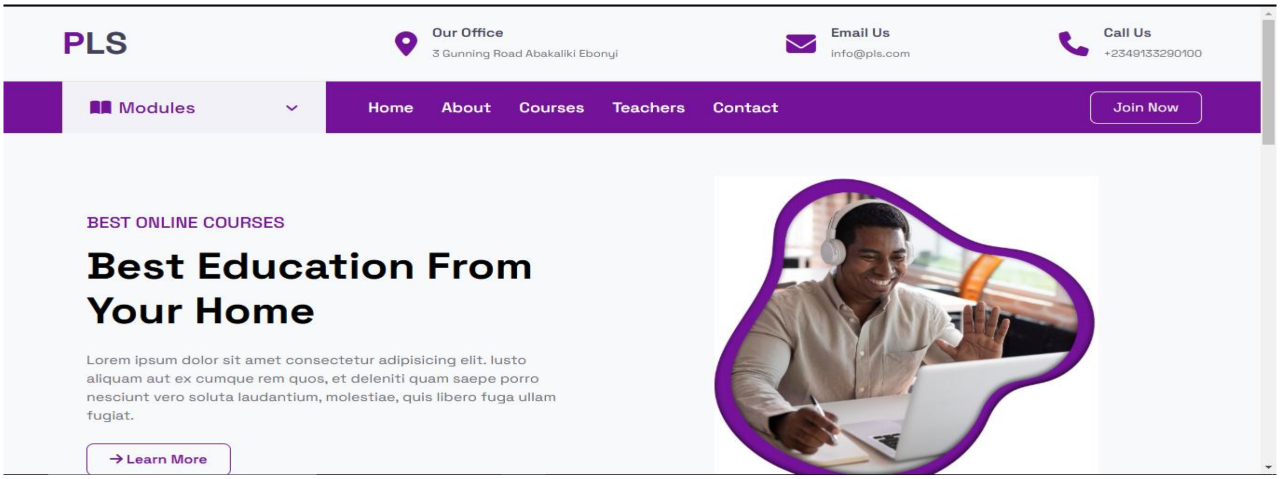

Figure 3: Home Page Implementation

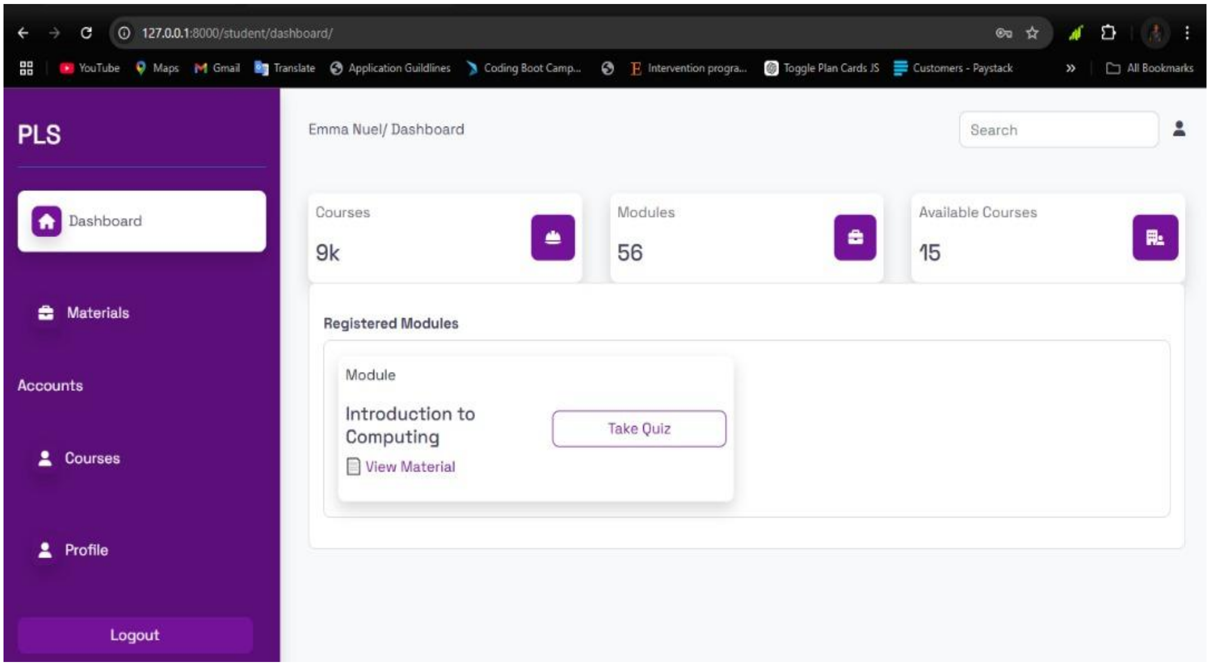

Figure 4: Student Dashboard Implementation

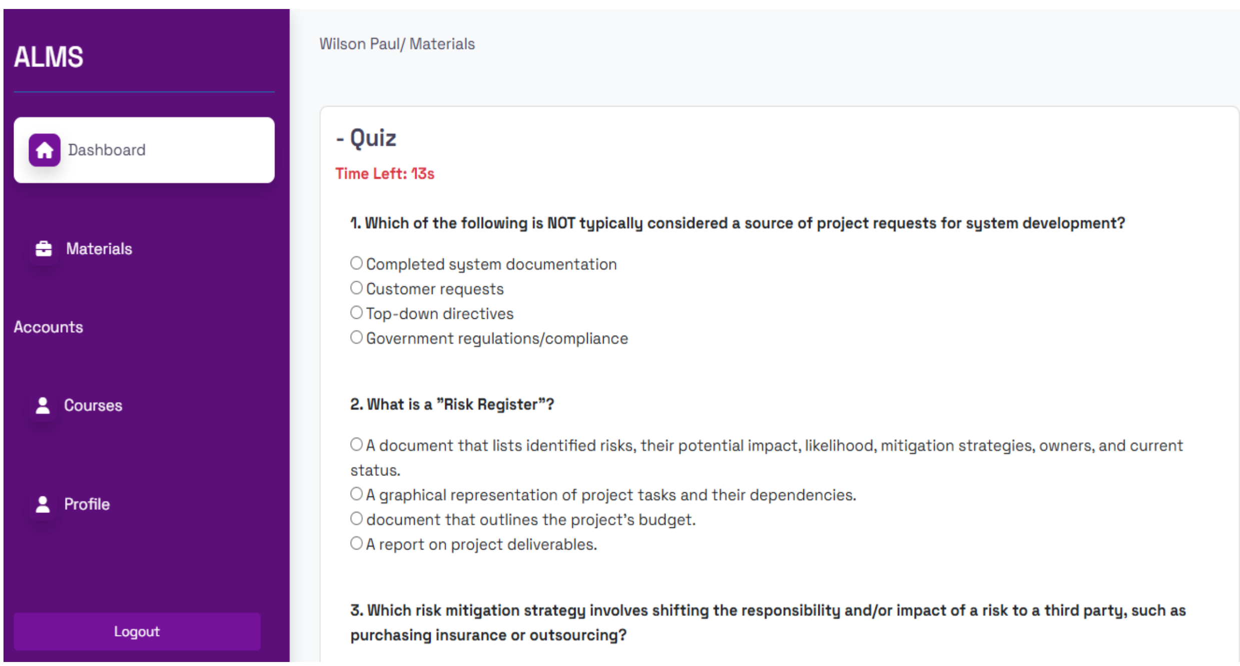

Figure 5: CBT Module Implementation

The system's 93% personalization accuracy aligns with findings from Singh *et al.* (2023) and Chen *et al.* (2022), demonstrating BERT's effectiveness in content recommendation. Real-time adaptability addresses gaps in traditional LMS (Harrer *et al.*, 2019), while the modular design enhances scalability (Morse & Cheek, 2020). However, challenges include ensuring data privacy

(Jobin & Vayena, 2019) and integrating with legacy systems (Ouyang & Jiao, 2021). The system's performance under high loads confirms its potential for widespread adoption (Nakamura *et al.,* 2022).

Performance Evaluation

The performance of the AI-driven Adaptive learning management system was assessed using the following key metrics:

i. Response Time**:** The system achieved an average response time of 1.2 seconds, meeting the target of less than 2 seconds. This ensured a smooth user experience during interactions and content loading.

ii. Accuracy of Personalization**:** The system demonstrated a 93% accuracy in delivering relevant learning recommendations based on user performance and feedback. This indicates the effectiveness of the adaptive algorithms in tailoring content to individual needs.

iii. System Stability and Scalability: During load testing, the system supported up to 200 concurrent users without crashes or performance degradation. This confirmed its ability to handle high user activity while maintaining stability.

Conclusion

This study successfully developed an AI-driven adaptive LMS that leverages data analytics and BERT-based NLP to deliver personalized learning experiences. By addressing limitations in traditional LMS—such as static pathways and limited adaptability—the system enhances engagement, comprehension, and equity (Ouyang & Jiao, 2021; Beck & Chisholm, 2020). The integration of real-time analytics, modular course structures, and intelligent remediation aligns with educational theories like Constructivism and Connectivism (Sevakula *et al.,* 2020; Ouyang & Jiao, 2021). Future enhancements should focus on ethical data handling, advanced AI techniques, and broader scalability to diverse contexts (Jobin & Vayena, 2019; Pathak et al., 2024). To ensure the sustained success and scalability of the AI-driven adaptive learning management system, several recommendations are proposed for its stakeholders. Learners should actively engage with the system's personalized learning pathways, which are designed to address individual knowledge gaps and enhance comprehension, thereby optimizing their learning outcomes (Shute & Ventura, 2019). Administrators are encouraged to harness the system's robust data analytics capabilities to inform strategic planning and optimize resource allocation, enabling data-driven decision-making that enhances institutional effectiveness (Johnson et al., 2016). Educators should leverage the system's data-driven insights to implement targeted interventions and refine teaching methods, fostering improved student engagement and academic achievement (Kagiyama *et al.,* 2019). For future development, researchers should explore advanced techniques such as reinforcement learning and explainable AI to enhance system transparency and user adoption, addressing ethical and practical challenges (Momin, 2023; Pathak *et al.,* 2024). Finally, all users—learners, educators, and administrators—are urged to provide continuous feedback to refine the system's usability and effectiveness, ensuring it remains responsive to evolving educational needs (Nakamura *et al.,* 2022).

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