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Development of a Mobile Learning Support System

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Abstract- The traditional one-size-fits-all education system overlooks the diversity in students' interests, learning preferences, and challenges, which limits the potential for engaging and effective learning. This highlights the need for a mobile learning support system to address these inefficiencies. This study presents a mobile learning system that uses the VAK learning model, enabling teachers to tailor curriculum content and exams to match each student's learning style. By utilizing cloud computing, the system provides convenient, anytime access, boosting both teacher and student productivity.

Indexed Terms— Adaptive, Cloud, Learning, Mobile, Personalized

I. INTRODUCTION

The rapid evolution of technology has transformed various aspects of society, but traditional educational systems remain unchanged. Conventional education follows a rigid structure, neglecting individual learners' interests, learning styles, and obstacles. However, disruptive technologies have revolutionized the educational landscape. E-learning technology has been integrated into schools, universities, and learning environments to enhance education standards. This innovation addresses the limitations of traditional classroom settings, providing flexibility and accessibility for learners who face challenges attending in-person classes (Boyinbode & Akintade, 2015). With learners increasingly familiar with computers and the Internet from a young age, there is growing interest in incorporating learning styles into technology-assisted learning (Radwan, 2013).

Personalized learning involves customizing training programs to suit individual needs, including goals, skill levels, learning style preferences, and progress monitoring. Adaptive e-learning systems recognize learner profiles and offer tailored learning paths. These systems enable students to select materials aligning with their learning style, profile, interests, and knowledge (Qazdar et al., 2015). This adaptive learning platform mirrors a medical consultation's empathetic and diagnostic approach, delivering tailored educational solutions that align with each student's needs and goals.

Researchers have developed various learning support systems, with Moodle being the most widely used. These systems are generally automated, relying on data collection to make decisions and adapting to learners' real-time needs by providing personalized content and activities based on individual characteristics (Peng, Ma, and Spector 2019; Qazdar et al. 2015; Wongwatkit et al. 2016). Unlike previous designs, the system implemented in this study incorporates mobile cloud computing, creating a more robust and flexible support system that can easily be scaled to larger learning environments.

II. REVIEW OF RELATED WORKS

In 2016, Wongwatkit et al. created a personalized learning support system to enhance physics students' learning experiences and results. The study sought to establish a dynamic mastery learning framework that continuously monitored student progress and adapted learning activities based on their performance. However, the system faced challenges tracking students' learning styles, motivational factors, and diverse learning outcomes across different platforms.

Radwan's 2014 study introduced an adaptive e-learning platform that adjusted learning elements to suit individual learners' traits. The system aimed to optimize online learning by recognizing learners' preferences across multiple learning style dimensions and matching personality assessments with relevant materials. However, limitations emerged in fully catering to diverse learner needs.

Also, in 2015, Qazdar et al. proposed a novel approach to enhance LMS functionality by integrating AeLF with ALSs. This synergy aimed to provide adaptive learning solutions, accommodate individual learner differences and offer dynamic course sequencing. However, the system requires further development to overcome critical challenges.

Monika Rani et al.'s 2015 study initiated an ontological approach. In it, she introduced an adaptive, personalized e-learning system combining ontology, software agents, and cloud storage. The goal was to provide tailored learning experiences, overcoming traditional content distribution methods. While integrating the Felder-Silverman model, the system faced challenges in fully accommodating individual learning needs.

Gangi et al. (2015) presented a cloud computing-based e-learning framework to combat rising data storage costs. The framework harnesses cloud and mobile computing capabilities to minimize expenses and facilitate seamless deployment. Despite its potential, the proposed architecture had a significant shortcoming: it needed to incorporate mobile cloud computing, restricting its applicability to cloud-based e-learning systems only.

Like Monika Rani, Boyinbode et al. (2020) proposed an ontology-driven adaptive e-learning system, offering personalized content aligned with learners' needs. However, the system's adaptability is constrained by reliance on assessment test responses utilizing Item Response Theory.

In 2016, Rezaei and Montazer developed a novel adaptive grouping technique for e-learning systems, utilizing fuzzy grafting and snap-drift clustering algorithms. The goal was to improve grouping precision and facilitate personalized course suggestions aligned with learners' learning preferences.

Bhaskaran and Swaminathan's (2013) research focused on developing an adaptive learning model that supports personalized learning in both online and offline environments. The study employed the Intelligent Adaptive E-Learning system and KNN algorithm to address intermittent connectivity issues. Nevertheless, the investigation's limitations include the exclusive reliance on the KNN algorithm without comparative analysis of other algorithms.

Various studies have enhanced adaptive learning systems. Nurjanah (2016) proposed a hybrid recommendation approach, combining content-based and collaborative filtering. However, limitations exist in refining strong learner identification and expanding collaborative filtering. Similarly, Tzu-Chi Yang et al. (2013) developed an adaptive system that considers learning and cognitive styles yet faced restrictions due to sample size and focus on customized interfaces and materials.

III. SYSTEM ARCHITECTURE

The proposed mobile learning support system architecture outlines the design and interactions between its core components, as shown in Figure 1.

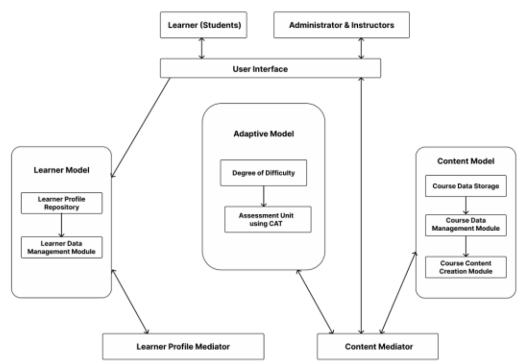

Figure 1. The architecture of the Mobile Learning Support System

A. The Learner Interface

The platform enables dynamic student-teacher interactions, while its interface orchestrates adaptive content delivery by the Adaptive Engine, guided by a structured model of user characteristics. Simultaneously, user responses are transmitted to the adaptive engine, updating the comprehensive learner profile that captures learners' distinctive characteristics during enrollment.

B. The Personalized Adaptive Engine

The present study's educational platform enables rich interactions between students and instructors. Using the adaptable engine and a structured user profile system, the platform delivers customized content based on learners' overall background and educational characteristics documented during enrollment.

C. *The Learner Profile Mediator*

The mediator is the single point of contact for request management and learner model repository administration.

D. *The Content Mediator*

This educational platform supports adaptive learning through its interface, which mediates interactions between students and teachers and informs the adaptable engine with user responses.

E. *The Learner Profile Repository*

This repository keeps each user's profile and actions and records their activities on their interfaces.

F. *The Learner Profile Model*

The system creates an adaptive user model that tracks relevant learner data to build each learner's profile, which is categorized into two main groups: learning profiles and user identification information. This study employs a Personal Information class to store identifying attributes and a separate learning profile framework to capture preferences, performance, skills, and learning styles. As a result, individual learners can demonstrate their learning performance by integrating prior knowledge with new information.

The "ability class" reflects the knowledge students have gained, assessed using item response theory. The VAK Learning Style Model (Fleming et al., 2006) is used in the "learning style class" to capture each student's learning preferences. Grounded in the VAK theory, which encompasses Visual, Auditory, and Kinesthetic dimensions of cognitive processing, the Learning Style class is structured within the Learning Category ontology to operationalize these dimensions systematically. Additionally, a carefully designed questionnaire based on the VAK taxonomy helps identify each learner's preferred learning modalities.

IV. IMPLEMENTATION AND RESULTS

The project aims to develop a cloud-based mobile learning support system that enhances students' educational experiences. The system uses a progressive web application to allow flexible, location-independent access for various stakeholders, such as administrators, instructors, and students. The platform's design caters to different user roles with corresponding functional capacities.

A. *System Requirements*

The requirements for this mobile cloud-based learning support system to function effectively include:

a. Cloud infrastructure: A scalable cloud infrastructure to host the application and provide storage and computing resources.
b. Database: A secure and scalable database storing user data and supporting real-time queries.
c. A Client-Side Application: This is responsible for providing the user interface, handling user interactions, sending requests to the backend, and displaying data. As a Progressive Web App (PWA), it also offers offline capabilities, improved performance, and a native app-like experience in the browser.
d. A Backend Server: Responsible for handling client-side requests from the mobile application, managing application logic, and communicating with the database.
e. Network connectivity: High-speed and reliable network connectivity to support data transfer and real-time communication between mobile devices and the cloud.

B. *Mobile Application Homepage*

The mobile application's homepage is the landing page, providing users with a concise overview of key features. An intuitive design and clear navigation elements create a positive first impression and guide learners through the application.

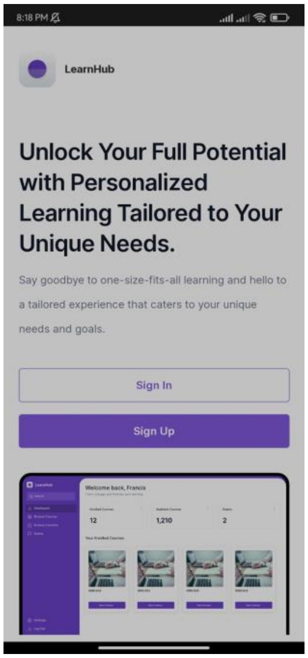

Figure 2. Mobile Application Homepage

C. Registration Page

The registration page enables new learners to sign up and enroll in courses. It usually requires submitting personal information such as name, email, and password. The user can access the system and its resources upon completing the registration process. The registration page is critical in securing the system by allowing only verified users to use it.

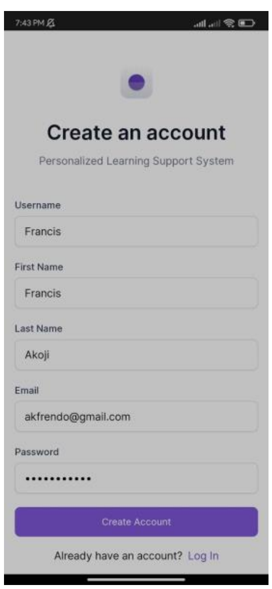

Figure 3. Registration Page

D. VAK Learning Style Detector Page

This page presents a list of questions for first-time users to determine their learning style, optimizing the delivery of suitable course content. The answers inform the identification of the user's preferred learning method, leading to a personalized and effective learning experience through tailored course material.

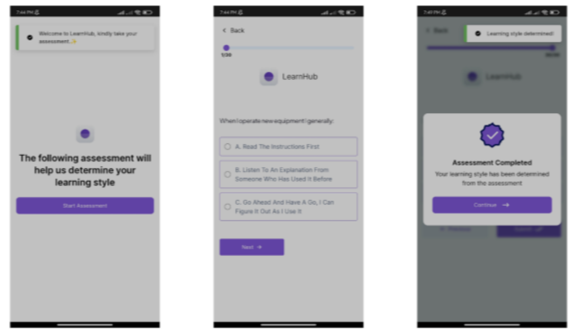

Figure 4. Learning Style Assessment Pages

E. User Dashboard

The user dashboard is a customized interface that displays relevant information and resources for the learner. It shows a list of available courses in the system, the learner's enrolled courses, and the learner's profile settings. The dashboard's user-friendly design provides quick access to essential information.

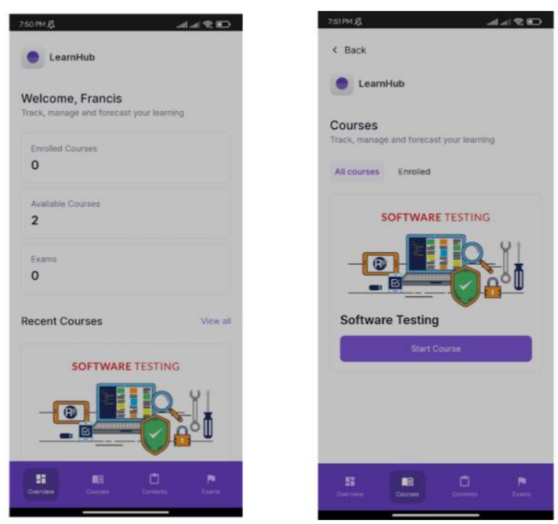

Figure 5. Learner's Dashboard

F. Learning Categories Page

When learners attempt to enroll in a course, this page assesses their skill level to ensure the learning experience is tailored to their needs. Beginners who are new to the subject or have little prior knowledge are provided with straightforward content that introduces the basics in an easy-to-understand way. Intermediate learners who have some familiarity with the subject receive more complex and challenging material that builds on their existing knowledge. For experts with a deep understanding, the system offers highly specialized and advanced content to enhance their learning.

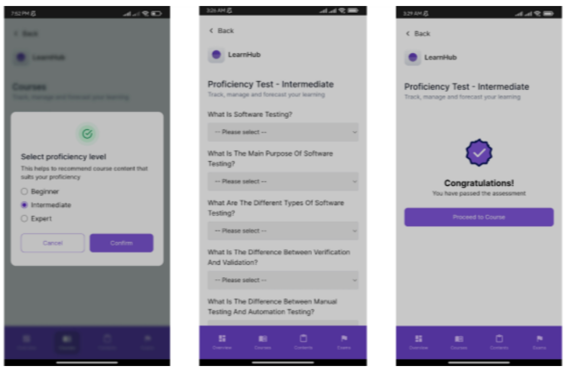

Figure 6. Learning Category and Proficiency Test

G. Course Contents Page

The course contents page displays materials tailored to the student's learning style. By presenting material in a format that aligns with the student's preferred learning method, the course contents page enhances the effectiveness of the learning experience.

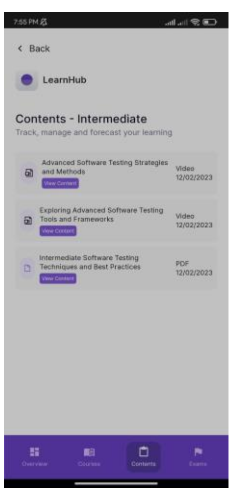

Figure 7. Personalized Contents for the Learner

H. Examination and Result Page

Course materials on the contents page are displayed based on the student's preferred learning method, enhancing the learning process by presenting information that aligns with their style. After registering, new users are asked to take an exam to assess their learning style, and the system customizes course content accordingly, using the stored information.

Returning users can access materials using their previously registered preferences, though they can retake the test to update or confirm their learning style.

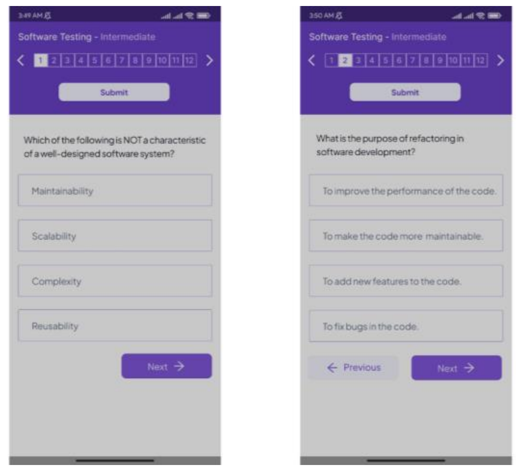

Figure 8. Examination for the Intermediate Level

The Learning Support System (LSS) has a user-friendly interface that makes it easy for users to browse courses, compare options, and enroll at the beginner level. After completing a course, users take a test to determine if they are ready to move to the intermediate level. New users who believe they have intermediate or expert-level skills can also take a test to see if they qualify for those levels.

They are encouraged to start at the beginner level if they fail to pass. The system gives two attempts for the eligibility test; if both fail, the user is advised to begin at the lowest level. The course offers three levels: Beginner, Intermediate, and Expert.

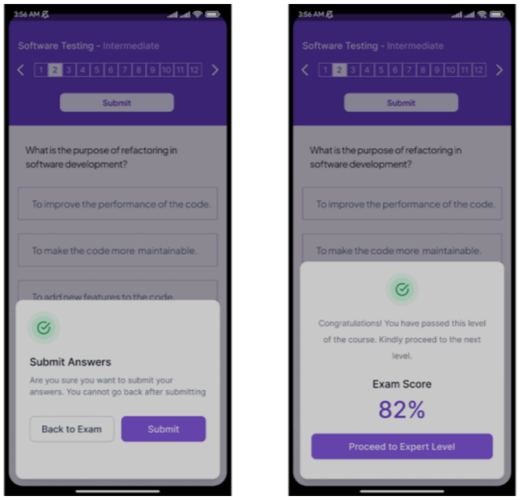

Figure 9. Showing A Learner Score and Qualification for The Next Level

Users will progress through the course levels based on their performance on tests and evaluations and learning styles and abilities. When a user enrolls at the beginner level, the system delivers content tailored to their learning preferences, skill level, and personal information.

Before taking an exam, users must view or download this customized content, which will be the basis for their assessment. Their scores on this exam will determine whether they can advance to the next level.

V. EVALUATION

For this case study, the Software Testing course was selected, a required course for third-year Information Technology students at the Federal University of Technology, Akure, Nigeria. The learning system was tailored to meet the needs of three learner categories: beginner, intermediate, and expert.

To assess its effectiveness, a study involving 20 participants compared the system's outcomes to traditional learning approaches, using average performance scores calculated from aggregated percentage scores at each level.

Table 1. Comparing the personalized system and the conventional system

S/N	PROFICIENCY LEVEL	MEAN PERFORMANCE
	Beginner	
1	Traditional Method	50
2	Personalized Adaptive	72
	Intermediate	
3	Traditional Method	52.5
4	Personalized Adaptive	66.4
	Expert	
1	Traditional Method	52.8
2	Personalized Adaptive	69.2

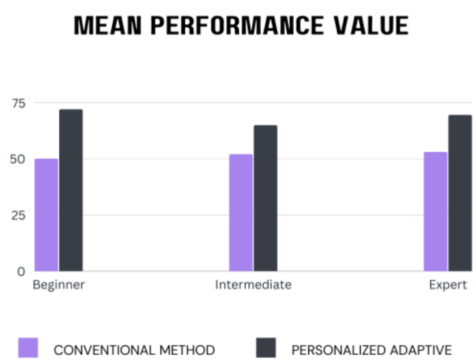

Figure 10. Mean Performance Value

A user-centered evaluation was conducted to gauge the system's performance, engaging 20 participants who had utilized the system. A tailored questionnaire elicited user feedback and perspectives on their system interaction experiences. The responses were analyzed to evaluate the system's effectiveness, usability, and performance. The outcomes of this analysis are presented in Table 2.

Table 2. Results of Analysis

S/N	REMARKS	EXCELLENT	SATISFACTORY	NEEDS IMPROVEMENT	POOR
1	Experience	14	4	2	0
2	Effectiveness	10	5	3	2
3	Accuracy	12	5	2	1
4	Usability	16	3	1	0

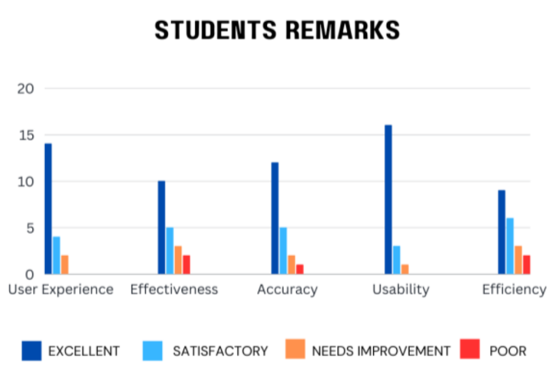

Figure 11. Overall Performance of the System

Figure 11 presents the system's evaluation results in terms of the above-listed remarks. The majority of users provided feedback indicating that the system was satisfactory. Therefore, based on the user feedback, the system performs adequately in terms of user experience, accuracy, efficiency, and effectiveness.

CONCLUSION

The design and implementation of a mobile learning support system have proven valuable for providing students with access to educational resources and materials. This study developed an intelligent, adaptive e-learning system that offers varied learning content tailored to students' learning styles in the Software Testing course (SEN 306). The system successfully enhanced students' learning rates and improved their understanding of testing concepts by matching content delivery with individual learning preferences.

Unlike conventional software testing course delivery methods, the system allowed students to take a learning style detector test to identify their preferred learning approach. Based on captured learning styles, the system delivered appropriate testing content. Examinations were conducted within specified timeframes to evaluate student performance and track improvements in their understanding of testing methodologies. The personalized adaptive e-learning system was tested using Software Testing (SEN 306) course materials with 20 users.

The results demonstrated that the personalized adaptive system achieved higher mean performance values at every level than conventional teaching methods, indicating superior efficiency in teaching software testing concepts. The system's evaluation revealed that a high percentage of user feedback fell between satisfactory and good, indicating strong acceptance of the system for learning software testing concepts and methodologies.

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