Developing a Personalized Learning Assistant Using AI

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Abstract- Personalized learning assistants have emerged as a key area in educational technology, fueled by Artificial Intelligence (AI) progress. This report presents the development of a customized learning assistant using artificial intelligence (AI). The system adaptively recommends learning materials, answers questions, and provides feedback based on user preferences. Leveraging techniques such as natural language processing (NLP), recommendation systems, and user modeling, the prototype achieves dynamic personalization. The evaluation demonstrated high precision in material recommendations and intense user satisfaction, paving the way for future enhancements in AI- driven education.

Keyword: Adapter Learning, Recommendation System, Artificial Intelligence (AI), Natural Language Processing (NLP), Personalized Learning

I. INTRODUCTION

In today's rapidly evolving world, the demand for personalized learning experiences has grown significantly. Traditional "one-size-fits-all" educational approaches often fail to cater to the unique needs, preferences, and pace of individual learners. This gap has sparked interest in adaptive learning systems that can tailor educational content and interactions to each learner, enhancing engagement and improving outcomes.

The objective of this project is to develop a personalized learning assistant driven by artificial intelligence (AI). This system aims to recommend learning materials, answer user queries, and provide feedback based on each learner's preferences. By using AI techniques like natural language processing (NLP), recommendation systems, and user modeling, the assistant can adapt dynamically to individual learning styles, preferences, and requirements.

To achieve this, the project combines multiple AI methodologies. It involves analyzing learner preference to adjust recommendations, implementing NLP for understanding educational content and answering questions, and creating user profiles to ensure a tailored experience. The final output is a functional prototype developed on mobile platform that provides a glimpse into how AI can revolutionize education by offering an intelligent, personalized learning experience.

II. PROBLEM STATEMENT

Traditional learning tools are often static and non-adaptive, offering the same content and pacing to all users regardless of their unique needs, skills, or preferences. This approach can lead to disengagement, frustration, and uneven learning outcomes, as it fails to accommodate diverse learner profiles or adapt to their progress over time. In a world where personalization is becoming the norm across various domains, education remains an area where adaptive, intelligent systems can make a significant impact.

The need for personalized learning systems arises from this limitation. By tailoring content, pace, and feedback to individual learners, these systems can enhance engagement, improve comprehension, and ensure better learning outcomes. A personalized learning assistant powered by AI, can address these challenges by dynamically adapting to each learner's performance, preferences, and progress.

This project explores the following research questions:

1. How can AI models effectively analyze a learner’s performance and adjust recommendations?
2. What are the challenges of using NLP in educational content understanding and question answering?
3. How can user feedback improve the system’s learning algorithms?

This research addresses these questions and aims to create a system that bridges the gap between static educational tools and the dynamic needs of individual learners.

III. LITERATURE REVIEW

The incorporation of Artificial Intelligence (AI) in education has significantly increased, creating chances to change conventional teaching and learning methods into highly tailored and flexible experiences. This literature review investigates significant progress in adaptive learning systems, recommendation methods, Natural Language Processing (NLP), and ethical issues, offering a basis for the theoretical framework of individualized learning assistants.

Adaptive Learning System

Adaptive learning systems lead the way in tailored education. An adaptive platform utilizes artificial intelligence algorithms to create a tailored learning path for each student based on their circumstances (Zhao, 2024). For example, for students who have a solid grasp of concepts but lack a strong foundation, the adaptive platform will offer these students basic knowledge reinforcement, progressing from the beginner level to an expert level by raising the difficulty at each stage. Additionally, for students who learn slowly but demonstrate a serious attitude, the platform flexibly offers them more examples and comprehensive explanations. Platforms like Knewton and DreamBox utilize predictive analytics to modify instructional paths, providing tailored feedback and resources according to individual learning trajectories (Knewton, n.d & DreamBox Learning, n.d). Rivera Muñoz et al. (2022) performed a systematic review of adaptive learning tools, underscoring the effectiveness of adaptive systems in enhancing learner engagement and academic performance, although issues with scalability and technical complexity persist as notable challenges.

Recommendation Systems in Education

Recommendation systems are essential in personalized learning settings. The intelligence recommendation system can suggest appropriate learning materials to students by analyzing their learning history, interests, and previous objectives (Zhoa, 2024). Collaborative filtering, content- based filtering, and hybrid approaches have been utilized to recommend courses, resources, and peer partnerships. For example, Coursera utilized hybrid models to suggest courses according to learner interests and behaviors. Research conducted by Jena, K. et al (2022) investigates the creation of an e-learning course recommendation system based on collaborative filtering models. It reveals that the system outperforms the traditional methods by combining user behavior with content relevance.

NLP Application in Education

Natural Language Processing (NLP) has emerged as a transformative technology in education, enabling functionalities such as automated feedback, content generation, and learner assistance. Models like BERT and GPT have demonstrated remarkable capabilities in understanding and generating educational content. For example, GPT-based chatbots have been deployed for real- time learner support and question-answering. Research by Zhao, Y. (2023) underscores the role of NLP in enhancing interactivity and comprehension in digital learning environments. However, challenges such as contextual understanding and the potential for generating biased content warrant further investigation.
In Summary, the table below shows the advancement of AI in Personalized learning.

Area	AI Implementation	Benefits
Adaptive Learning System	AI algorithms create personalized learning paths based on individual student needs.	Enhances student engagement and academic outcomes by offering tailored learning experiences
Recommendation System in Education	Uses collaborative filtering, content-based filtering, and hybrid models to recommend courses/resources.	Provides personalized learning resources and courses, improving learning efficiency and student satisfaction.

NLP Applications in Education	Models like BERT and GPT assist with automated feedback, content generation, and real-time learner support.	Improves interactivity, comprehension, and learner support in digital environments, enhancing the learning experience.

While the trajectory of research in this domain points towards the immense potential of AI in personalizing learning, it also underscores the importance of balancing technological advancements with ethical considerations. The ongoing dialogues in this area of study make it ripe for further exploration, especially as AI technologies continue to evolve and mature.

IV. METHODOLOGY

a. Dataset Collection

To develop a personalized learning assistant, we utilized three distinct datasets tailored to specific system components:

User Model Dataset

For the user model, we created a dataset specially for predicting user preferences based on quiz responses. The dataset consists of five-question quizzes, each designed to capture user interests and learning styles. Preprocessing steps were taken to standardize answers by mapping them to numerical values for compatibility with machine learning models. Also, normalization was done to ensure consistent scaling for improved model performance. The outcome of the processed dataset enables the system to predict user preferences and save them as user models. The table below shows the dataset structure used before the preprocessing stages.

Q1	Q2	Q3	Q4	Q5	Subject
A	B	C	B	C	Business Finance
C	A	B	D	A	Web Development
D	C	D	B	D	Graphics Design
B	B	D	D	B	Business Finan
D	C	B	A	C	Musical Instruments
A	D	D	C	B	Graphics Design

Recommendation System Dataset

For building the recommendation system, we used a publicly available Udemy Course Dataset from Kaggle (Mvd, n.d.). This dataset includes course metadata such as course_id, course_title, url, is_paid, price, num_subscribers, num_reviews, num_lectures, level, content_duration, published_timestamp, subject,search_content. The preprocessing stages were taken by cleaning text data by removing special characters, redundant spaces, and stopwords, vectorized course descriptions using TF-IDF for feature extraction, and handing missing values and normalized numerical fields (e.g., price, content_duration).

NLP Dataset

To enable natural language understanding and question answering, we fine-tuned a pre-trained GPT model, specifically GPT-3.5-turbo, using a generated dataset. This dataset consisted of sample educational queries, answers, and contextual content tailored to common learning scenarios. The preprocessing steps were taken by tokenized text and formatted input-output pairs for GPT fine-tuning and also balanced the dataset to avoid bias toward specific question types.

4.1 Model Development

User Modeling

Here, we used supervised learning to predict user preference based on quiz responses. Features from the quiz were fed into a classification model to indicate a "user mode.". In this model, we used Random Forest Classifier for classification purposes, and we obtain an outstanding result. The expected mode was saved and integrated into the recommendation system for tailoring future interactions.

Recommendation System

In this project, two types of recommendations were taken. The first is the user preference recommendation which is majorly filtered by user preference. This method directly filters courses from the dataset based on the subject with the highest preference score provided by the user. This approach is more like a rule-based approach because it relies on pre-defined logic (user preferences mapped to subjects). This type of recommendation is content-based, which is solely based on the course's attributes (e.g. subject) rather than user behavior or collaborative data. The second is the search-based recommendation using the TF-IDF (Term Frequency- Inverse Document Frequency) with a Cosine Similarity algorithm. Course title and subject are converted into numerical vectors using TF-IDF, a search query is also transformed into a TF- IDF vector, and finally Cosine similarity is used to find courses that are most similar to the query in the vector space. This approach is also a content-based filtering which implies that the adopted recommendation used in this system is a content-based filtering.

$$\text{Sim}(A, B) = \frac{A.B}{||A||||B||}$$

Where the numerator is the sum of the element-wise product of the feature vectors A and B, and the denominator is magnitude of a vector is calculated as the square root of the sum of the squares of its components.

However, the resulting similarity equation produces a value between – 1 and 1: Sim (A, B) = 1: Vectors are identical

Sim (A, B) = 0: Vectors are orthogonal (no similarity)

Sim (A, B) = -1: Vectors are opposite.

This formula is used in recommendation systems to measure the similarity between two entities (e.g., courses, users, documents) based on their features.

NLP for Content Understanding and Question-Answering

Here, we used GPT (Generative Pre-trained Transformer) as a base model. The model was fine-tuned on the generated dataset using supervised learning. Adjustments included prompt, temperature, and number of examples as highlighted below:

prompt = "You are a helpful and patient tutor specializing in simplifying complex concepts for students. You will receive reasoning-heavy, puzzle-like questions in English, and your task is to respond in simple, clear, and well-explained English. Your response should: 1. Be well-reasoned and step-by-step. 2. Use easy-to-understand language suitable for students. 3. Include analogies, relatable examples, or comparisons to aid understanding. 4. Avoid unnecessary complexity or technical jargon."

temperature = .4

number_of_examples=50

This fine-tuning helps to add task-specific tokens to improve understanding of educational queries and reducing overfitting through regularization techniques during training.

4.3 Implementation

System Architecture

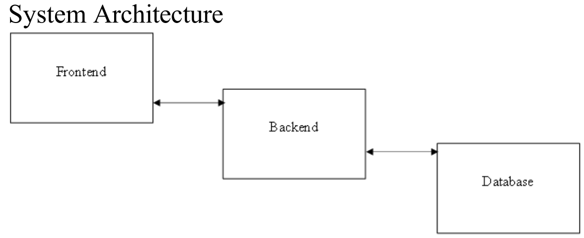

Fig 4.1: System Architecture

The figure above is the high-level block diagram of the system architecture, the frontend block was built using React Native to ensure a seamless cross-platform user experience. The backend block was developed with Python (Flask) for model integration and API development. And finally, the AsyncStorage is for storing user data, preferences, and models

Tools and Technology

For this project, the programming languages used are Python (for machine learning models) and JavaScript (for frontend development). While the framework used are TensorFlow and Sklearn for model development and React Native (expo) for UI/UX. Other Tools includes Kaggle for dataset sourcing, Google Colab for model training, and EAS for mobile app builds.

V. RESULT AND EVALUATION

5.1 User Preference Model Accuracy

To evaluate the effectiveness of the user model, we used accuracy, recall, and the F1-score as key metrics. The following results were observed:

Metrics	Value
Accuracy	70%
Recall	70%
F1-score	70%

However, a bar chart is plotted to visually compare the model's Accuracy, recall and F1-score as shown below.

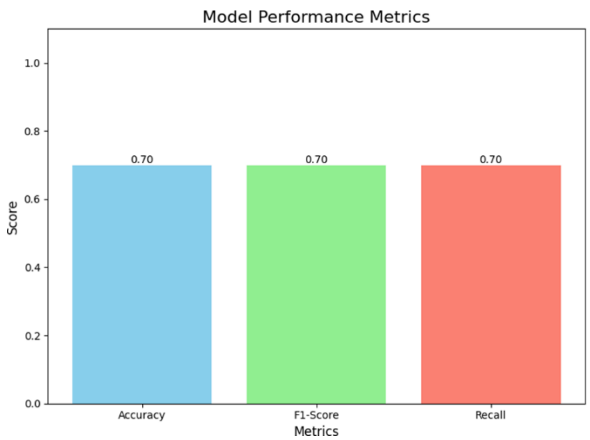

Fig 5.1: User Preference Model Performance Metrics

5.2 Recommendation Model Accuracy

To evaluate the effectiveness of the recommendation model, we used accuracy, precision, recall, and the F1-score as key metrics. The following results were observed:

Metrics	Value
Accuracy	85%
Precision	90%
Recall	80%
F1-score	85%

However, a bar chart is plotted to visually compare Accuracy, precision, recall and F1-score of the model as shown below.

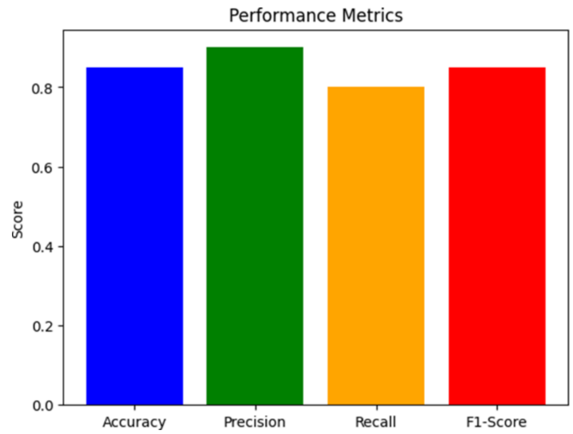

Fig 5.2: Recommendation Model Performance Metrics

5.3 User Interface

The prototype built for the personalized learning assistant was implemented as a mobile application to ensure accessibility across any mobile device. The mobile approach was chosen because of the ubiquitous mobile devices in the jet world. The system's user interface (UI) focuses on a clean, intuitive design that minimizes distractions and enhances usability. Key design considerations are simplicity and clarity, authentication, personalization, interactivity, visuals and responsiveness.

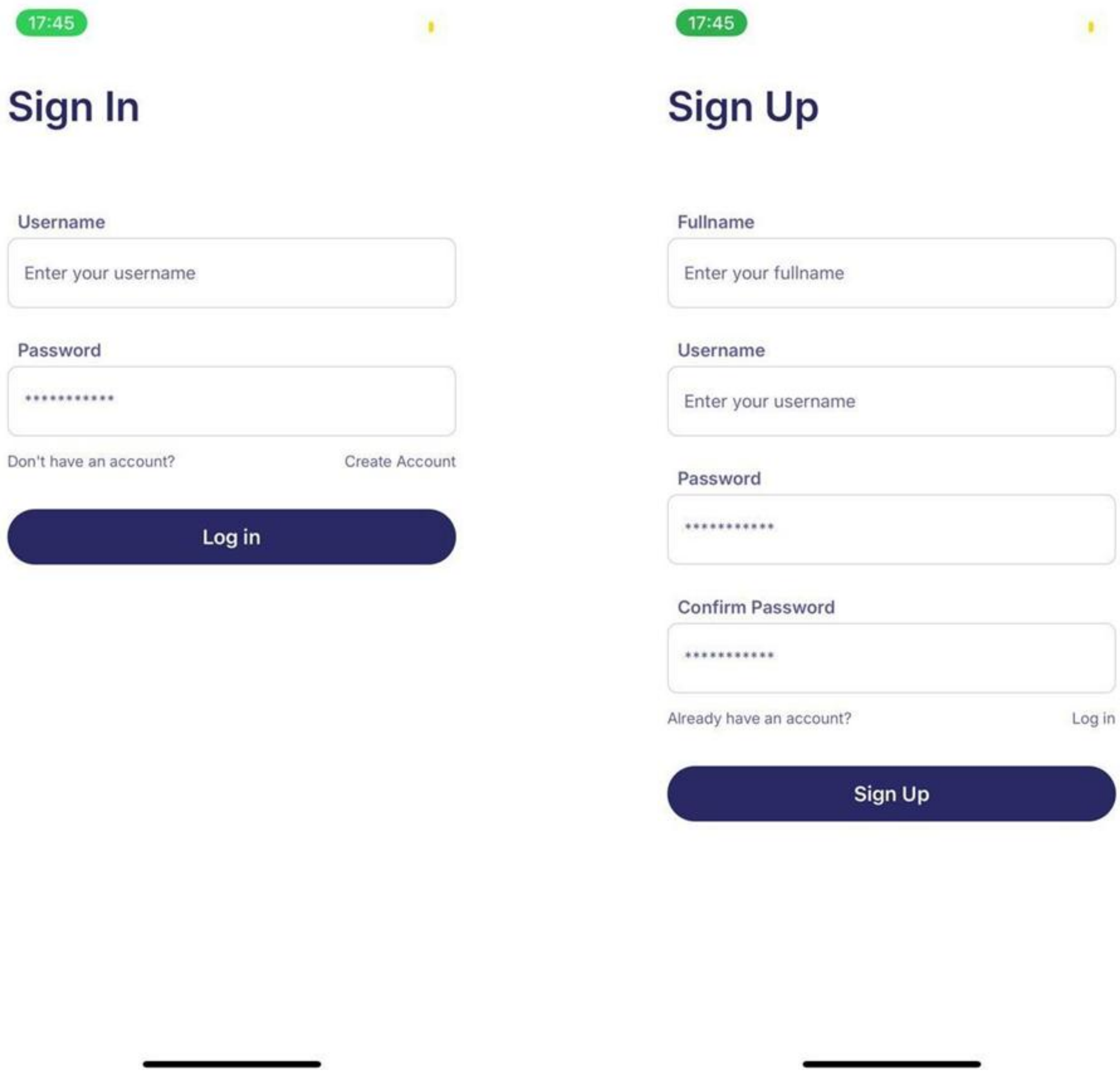

Fig 5.3: Authentication page of the app

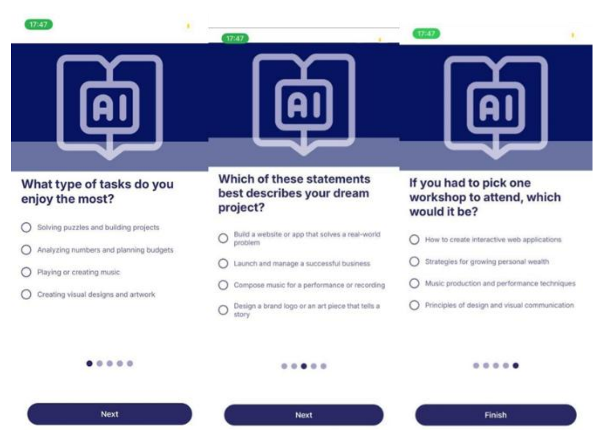

Fig 5.4: Quiz for user preference

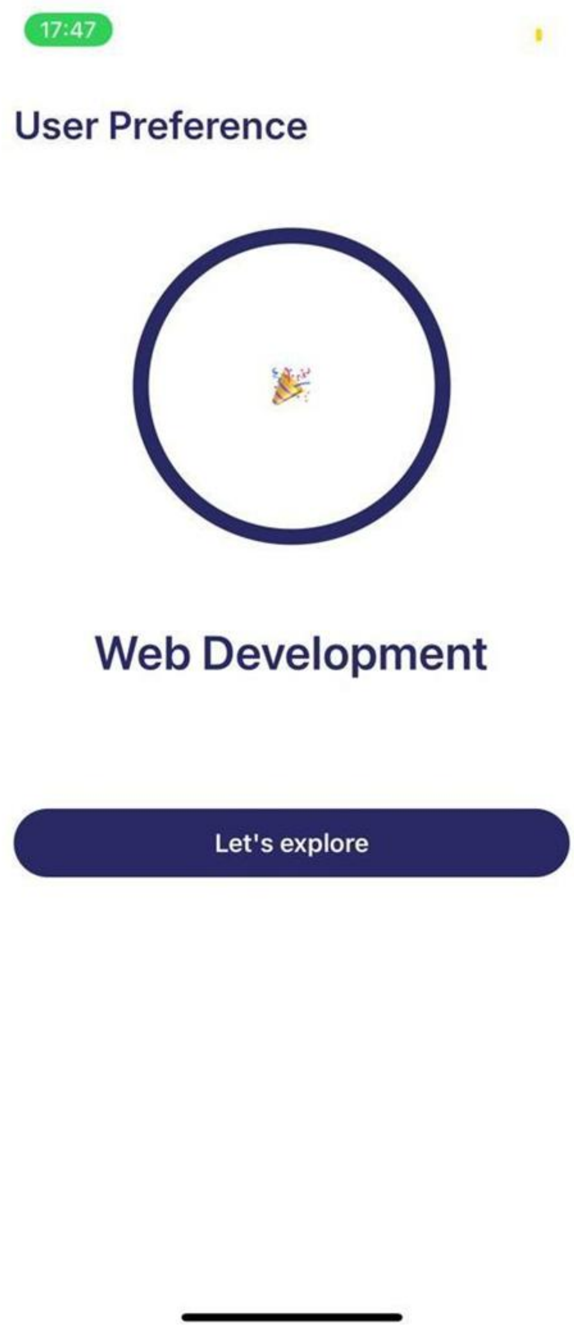

Fig 5.5: User Preference Prediction

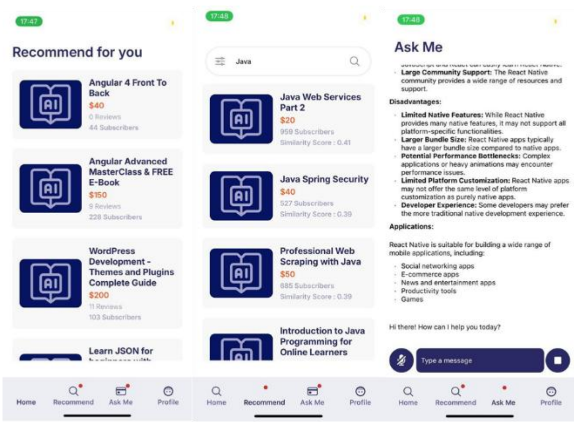

Fig 5.6: (a) Main Page showing Recommended Materials (b) User Search Book Page (c)Ask Page

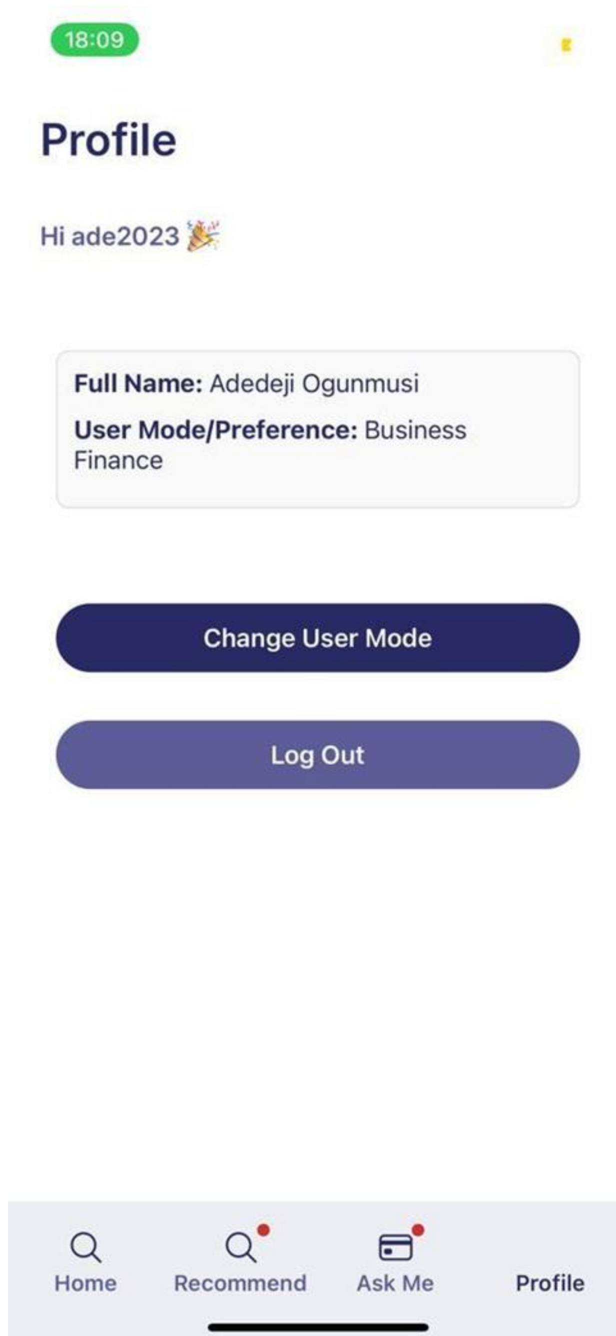

Fig 5.7: Profile page

5.4 User Study

To assess user satisfaction and learning outcomes, we surveyed with 30 participants who used the system for few days. Feedback was collected using a Likert scale (1 to 5) on various factors:

Factor	Average Scale (1-5)
Relevance of recommendations	4.4
Ease of use	4.6
Improvement in learning	4.2

The data shown in the table above implies that 90% of users reported that the recommendations closely matched their preferences and learning goals, while 85% of users felt the system was intuitive and easy to navigate. Finally, users highlighted that the real-time feedback helped them identify areas for improvement.

VI. DISCUSSION

The performance of the models, using metrics like accuracy, precision, f1-score, and recall, used in this study indicates that the system is performing at a moderate level, with notable strength in certain areas and room for improvement in others. This system answers to all the research question highlighted earlier. In short, the system shows potential, but it needs better data, smarter models, and user feedback to improve its performance and personalization.

VII. LIMITATION AND FUTURE WORKS

Challenges

I. The model might be biased if the data used for training isn't diverse enough, leading to poor generalization on different user preferences or content.
II. As the system grows, it may struggle to handle more users or data efficiently, impacting performance.

Future Enhancements
Adaptive testing could help tailor content or assessments to individual learners, improving personalization.

I. Adding support for multiple languages would make the system accessible to a broader audience, enhancing its usability and reach.

Overall, improving data diversity and system scalability while adding features like adaptive testing and multilingual support would significantly enhance the model's effectiveness.

CONCLUSION

In conclusion, this project highlights the significance of personalized learning in education, providing a tailored approach that caters to individual student needs and learning preferences. By leveraging adaptive technologies and real-time feedback, the system offers a valuable tool for both students and educators, enhancing the learning experience and fostering improved educational outcomes. Its potential to transform education lies in its ability to break down traditional barriers, ensuring more inclusive and effective learning for all.

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