AI Driven Interactive Learning Platform: A Systematic Approach to Personalized Learning and Persona-Based Content Delivery

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Abstract **— Education is evolving with the integration of artificial intelligence, offering opportunities for enhanced personalization and learner engagement. However, many learners struggle with finding tailored support that matches their individual preferences and motivations. This paper presents an AI-powered interactive learning platform that uses information and character models for creating effective and interactive learning scenarios related to different real and fictional personalities. Constructed to maintain interest based on typical and motivational modes of learning, all the personas regulate their answer choices based on learner type, mode of learning and preferences all in real time. The system introduces adaptation based on a Large Language Model trained in various data types, thus optimizing engagement, satisfaction and learning retention. In terms of retrieval-augmented generation, it dynamically responds to users being capable of providing answers from apparently diverse personality characteristics and of teaching methods for the different learning styles of the majority of users. AI features of the system include adaptability, engagement profiles and response analytics that makes the educational environment both engaging and continuously responsive. This work examines the creation and deployment of persona-based AI in learning environments while also highlighting how the technology could improve teaching and training experiences with intelligent and adaptive communication skills.**

Keywords — Adaptive learning platform, AI-powered learning platform, GenAI, Interactive learning, Large Language Models, Persona-based education, Personalized learning, Retrieval-Augmented Generation.

I. INTRODUCTION

In recent years, AI has significantly influenced digital learning enabling learners to realize the needs of the learning process. In most representative conventional online learning models, there is no or limited interaction between the student and contents; as such the content delivery is mostly static and may not be friendly enough to suit individual learning needs. This causes a problem as learners cannot relate to most content they come across, their motivation, retention and overall learning experience is negatively affected.

This paper introduces an AI-driven learning approach that utilizes a persona-based interaction strategy are proposed to increase consumer interactions and satisfaction in digital learning environment. As with the application representing well-known personalities and fictional characters: Virat Kohli, Shah Rukh Khan, Doraemon and Steve Jobs, the application adapts to the requirements of students of different ages and knowledge levels. This approach is interesting and realistic because each persona has distinct attributes and ways of communication. The system employs a LLM that has been fine-tuned to use various datasets to make responses for retrieval and generation that vary depending on the user's inputs, to give real-time, relevant feedbacks in accordance with the learner's preference [8].

The objective of this research is to explore the potential of persona-based AI in the contexts of learner engagement and personalization. With regards to quantitative assessment, the effectiveness of persona-based interactions in supporting an engaging and adaptive environment of learning will be evaluated based on results from response accuracy, session duration, user satisfaction and adaptability. Implications from this study provide an understanding of how persona-driven AI may help learning styles and outline the development of subsequent, digital learning environments suggests the possibility of change through persona-driven AI learning.

In Section I, we introduce the AI-powered learning platform, designed to enhance educational engagement through persona-driven interactions. Utilizing RAG and LLM model, the system dynamically adapts responses based on distinct personas, providing users with tailored learning experiences [9]. The rest of the paper is organized as follows: Section II reviews related literature on AI-driven personalized education. In Section III, we discuss the methodology, including the system architecture, LLM fine-tuning and persona-specific adaptations. Section IV covers the analysis of results and Section V concludes the research study.

II. LITERATURE REVIEW

In research paper [1], the study focuses on AI-enabled learning systems that investigate alternative frameworks and models for language and programming instruction, employing Bayesian and neural network approaches. However, many of these technologies are still in development and have minimal commercial potential. One major criticism is that it does not meet advanced learning needs, which leaves clients struggling with the technology. The project's purpose is to overcome these gaps by analyzing existing AI systems and inventing novel classroom applications, resulting in increased student engagement and learning outcomes.

According to Baillifard et al. [2], AI-powered tutoring systems can potentially improve customised learning, user engagement and academic performance. Immediate feedback, spaced repetition and dynamic engagement are all effective methods for capturing student attention. However, problems arise when AI lacks sufficient personalisation, leading in disengagement and poor learning outcomes. According to study, platforms that do not deliver real-time feedback or engaging conversational interfaces do poorly. AI-powered celebrity lecturers, for example, provide a way around these limits, potentially increasing engagement and improving educational achievements.

In [3], Girija Attigeri et al. presents a chatbot for engineering college admissions was developed to handle a high volume of queries from students and parents throughout the counselling process. It accurately responds to client questions utilising pattern matching, TF-IDF vectorisation and neural networks. This model, known as Hercules, outperformed others because to its sequential modelling and optimisation approaches, which provided 24-hour support, combated misinformation and improved user experience.

In [4], researchers evaluated the effectiveness of two AI chatbots, Bard by ChatGPT-3.5 and by administering a 90-query survey to 46 emergency medicine residents. While Bard scored 55.5% with 50 correct answers, ChatGPT-3.5 achieved 60% accuracy by answering 54 questions correctly. While both models did well in endocrine illnesses, they struggled with digestive problems and ECG interpretation. These results highlight the need for additional study to improve AI models' effectiveness in emergency medical scenarios and cast doubt on their trustworthiness in medical education.

McGrath C. et al. in [5], presents the impact of chatbots driven by generative AI on procedures in higher education was examined. The work adds to the theoretical body of work to correct for tendency of prior literature to hyperbolise the potential of these technologies. As much as chatbots provide for the learners, some questions arise as to how they impact equity and learners' engagement across learning communities. The authors suggest using the form of qualitative research so that the difficulties and changes experienced by GAI chatbots and related educational stakeholders can be better understood clearly.

The research conducted by Shahri et al. [6] focused on evaluating the potential of GPT-4 as an AI-powered tutoring system for delivering personalized education. Their work aimed at exploring the possibility of applying the concept of the advanced language model, GPT-4, to educational practice. The researchers aimed to bridge the gap for the effectiveness of the system in delivering tutor-specific instruction in a student-centered approach and in delivering feedback in real-time. Their work was focused on trying to bring the traditional education paradigm closer to the new age personalized learning based on AI technology and the main goal was to advance education through technology [14].

Frank et al. [7] has discussed the effectiveness of Large Language Models to design an Intelligent Tutoring System for R programming education for teaching learners at personalized level with feedback and learning path preference. Their studies compared different language models as a way of identifying the most suitable strategies towards the deployment of artificial intelligence enabled programming tutoring system [19].

III. METHODOLOGY

The intervention of this research is to develop an AI based interactive learning platform as illustrated below in fig 1 which will help in making online learning more personalized and engaging. The platform leverages a MiniLM transformer for vectorization and integrates LLM for content transformation techniques. The system produces the course modules according to the user queries and then applies the personas to amend the modules. The methodology is entirely based on the fusion of technologies like Django for the backend, React for the front end or the user interface, while LLM namely Google's Gemma Model as the power that steers the AI-based conversation. This combination makes the

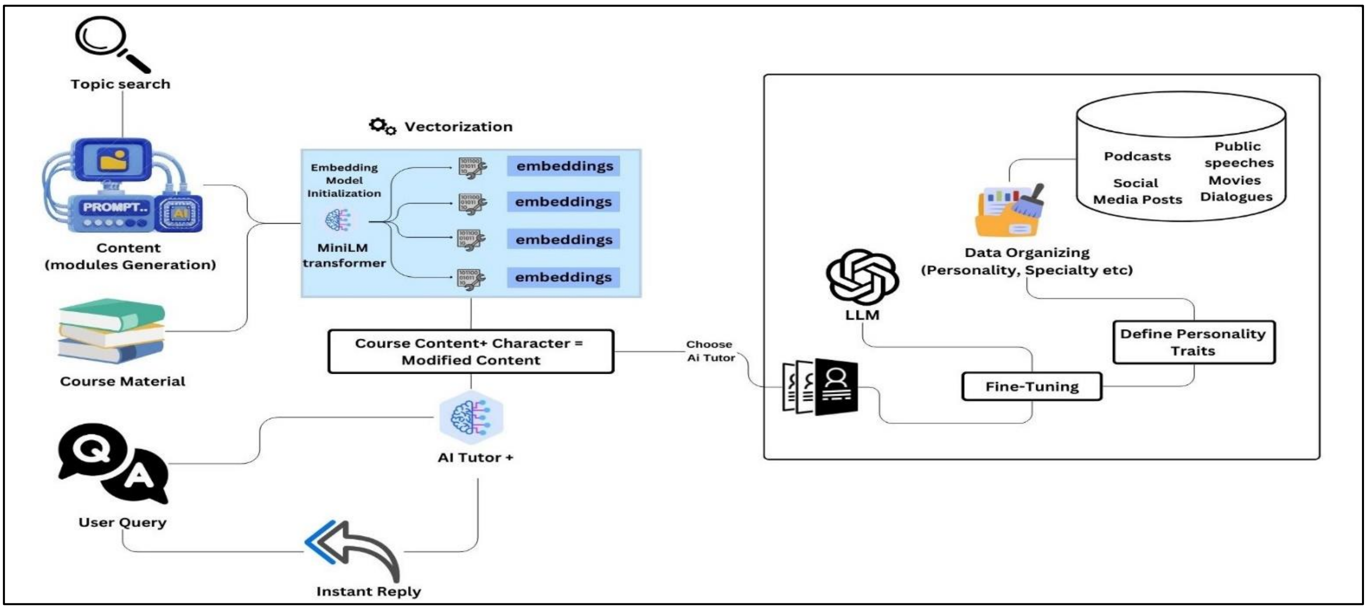

Fig. 1. System Architecture

system highly scalable and easy for the users to navigate while at the same time being capable of handling highly complex learning queries [13]. To have a thorough understanding of its functionality, we will look at the system architecture, content generation process, data embedding strategies, LLM fine-tuning and evaluation strategy for determining its impact on learning results. The architecture diagram, in fig.1, illustrates the components and flow of data within the System, designed to create a persona-based, interactive learning experience for users. This architecture integrates key modules for content processing, personality modeling and interactive user response, aiming to deliver an AI-driven educational assistant that is both informative and engaging [10]. The steps in this process are outlined below.

A. Input Module

In the initial stage, users enter the desired topic through a chat interface as well as audio input. This input is processed using Natural Language Processing algorithms, which identify the requested topic in the system. The input is mapped to the available topics in the database using a semantic similarity model. If the topic exists, the system progresses to generate relevant learning modules.

Equation 1: Semantic Similarity Score Calculation

The similarity between the user's input and stored topics is calculated using cosine similarity:

$$Similarity\ Score = \frac{\sum_{i-1}^{n} A_i B_i}{\sqrt{\sum_{i-1}^{n} A_i^2} \times \sqrt{\sum_{i-1}^{n} B_i^2}} \qquad (1)$$

Where A and B are vector representations of the user's input and stored topics, respectively. This ensures that the topic chosen by the user matches one of the pre-defined subjects in the system. An interface powered by Django manages the user input, enabling seamless topic identification.

B. Database Module

The project involves collecting large volumes of data from podcasts, social media, speeches and movie dialogues, among other activities, to create a strong knowledge base. This data is employed to predict personality and to fine-tuned the LLM for the given types. This helps to the development of an interactive learning platform that reacts based on the characteristics laid down. The content database is structured into three main layers: topic categories, specific modules and AI tutors. As for the learning modules of the selected topic, the listing is retrieved from the database. Each AI tutor is pre-trained with distinct response models, reflecting the persona of the tutor. The database also maintains the record of the conversation such as log, history etc to enhance user related data over the period as shown in fig 2. Every tutor is fine-tuned using Google's Gemma Model and the conversation that the user had with the tutor will be recorded for future use.

Equation 2: Data Retrieval Query

The system queries the database to retrieve modules based on user-selected topics:

$$Module\ Set = \{M_1, M_2, \ldots., M_n\} \qquad (2)$$

Where M is the ith learning module associated with the chosen topic.

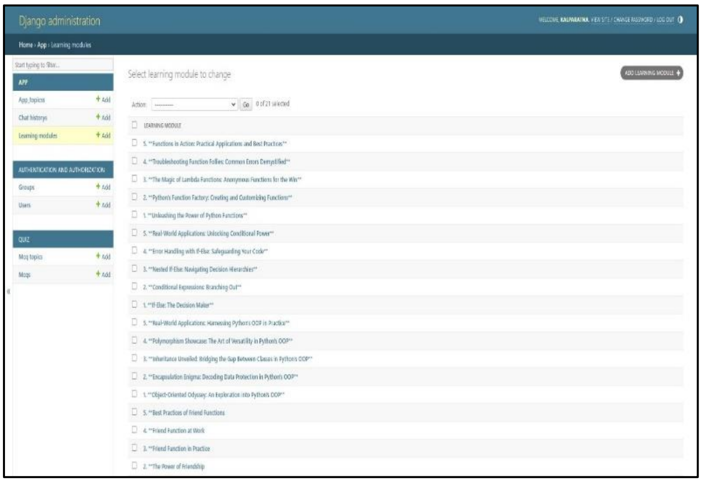

Fig. 2. Database Structure

C. AI Tutor Selection Module

Users select their AI tutor from a list of available personas, each fine-tuned to respond with a specific style. The system utilizes a Transformer-based architecture for generating responses in real-time. After selecting a tutor, the fine-tuned model associated with the tutor is loaded and the conversation begins.

Equation 3: Tutor Selection and Response Generation

The response from the AI tutor is generated using the fine-tuned language model LM_t as follows:

$$R_t = LM_t(Q) \qquad (3)$$

Where R_t is the tutor's response and Q is the user's question. Each AI tutor's response R_t depends on their training, which captures both the knowledge domain and personality traits.

D. Fine-Tuning Process

In the system, the external data feeds include podcasts, speeches and social media posts that help to infer the personality traits of the AI tutor [11]. As shown in fig 3, the LLM is fine-tuned using large amounts of data, including the organized personality-specific data, to ensure it behaves as designed. The fine-tuning process adjusts LLMs parameters, so that it can mimic human like interactions and respond to the personality traits defined earlier in the system. This process ensures that the interaction between the AI tutor and the user continues to match the user expectations. The LLM is fine tuned to match the exact traits necessary, ensuring that the AI tutor will always behave in the same way based on predefined persona. The fine-tuning process is done by training each AI tutor to their model over dataset that is specific to their persona, adjusting its weight with the help of supervised learning to anticipate the correct answer, aligned with the tutor's personality and domain knowledge.

Equation 4: Fine-Tuning Loss Function

The loss function used during fine-tuning is calculated as:

$$L(\theta) = \frac{1}{N}\sum_{i-1}^{N}\left(y_i - f(x_i,\theta)\right)^2 \qquad (4)$$

Were,

- $L(\theta)$ is the loss,
- y_i is the true label for response i,
- $f(x_i, \theta)$ is the predicted response for input x_i,
- N is the number of training samples.

The process optimizes the model's parameters θ to minimize this loss, improving the relevance and accuracy of the AI tutor's responses.

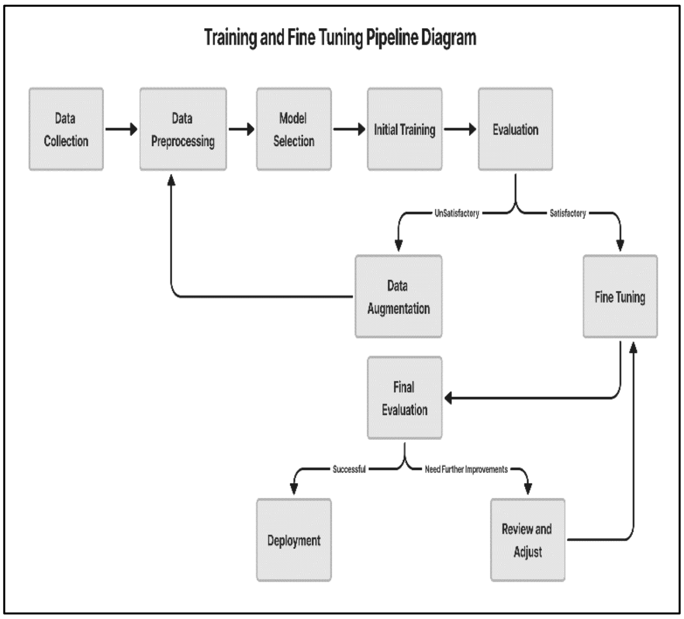

Fig. 3. Training and Fine-Tuning Pipeline

E. Content Generation and Personalization

- **Content Generation and Topic Search:** There is an initial "PROMPT" that creates content from the user searches and course content accordingly. This module employs topic search to get pertinent contents for learning modules and further, constructs learning content adaptively based on the needs of the learner.
- **Vectorization Using MiniLM Transformer:** The next step is vectorization of the generated content, MiniLM transformer is used to obtain the embedding [16]. These embeddings convert the textual data into numerical signs, which make the knowledge machine-readable. This is because it enables the system to use the aspects of machine learning models for personalization.
- **Character-Based Content Personalization:** Another interesting feature within the system is the option to adapt the contents depending on a certain character of the person. In the "Course Content + Character = Modified Content" block, learning modules are transformed in terms of the defined personas in order to enhance the relevancy of the content for the learners.
- **Embedding Initialization and Training:** The generation of embeddings is based on the use of the MiniLM transformer. These are the facts that are learned from the course materials and from other data sources through which the machine learning models are trained. This phase helps to personalized the content as well as to ensure that the content presented is within the familiarity level of the user and meets the intended learning goals.

F. Learning Delivery

After selecting the tutor, the learning content is delivered in modules as shown in fig 4. Each module is presented as a conversation between the user and the AI tutor [18], with the tutor offering detailed explanations and clarifications.

Equation 5: Module Completion Check

At the end of each module, the system checks if the user has understood the content using feedback-based mechanisms. The completion score is calculated as:

$$C = \frac{\sum_{i-1}^{m} u_i}{m} \qquad (5)$$

Were,

- C is the completion score,
- u_i is the user feedback for the i-th module,
- m is the total number of modules in the topic.

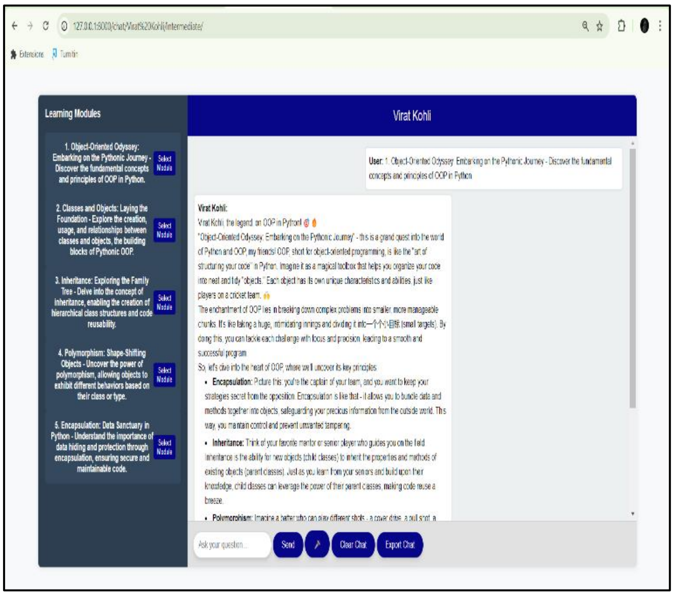

Fig. 4. Learning Interface

G. Question-Answer Interaction

During learning session, users can follow up on questions in real time. The system gives immediate responses based on the fine-tuned model. The interaction is dynamic, since the tutor is able to change the way, they explain or answer questions in order to capture the user's attention [12]. The system is designed to solve complex, context-dependent questions using multi-turn dialogues. It also allows the conversation to progress coherently across multiple user interactions.

- **Query Responses:** The AI tutor powered by LLM, accepts user query and processes it and responds immediately having analyzed the user-specific content made earlier. This interactive module provides the ability to provide instant feedback and answers in dual language to users queries [17], creating an engaging and real-time learning experience.

- **User Interaction Layer:** The architecture provides the necessary user interaction layer where the user can search topic and ask queries. The queries are then solved by the AI tutor, which responds with personalized and contextually relevant content [15]. It also allows for immediate exchange which means that the learning process and feedback is constant and effectively makes the system very user-specific.
- **Real-time Personalization:** One of the standout features of the system is its ability to perform real-time personalization. As users interact with the system, it dynamically adapts the course content using the pre-defined characters. This customization ensures that the learners engage with the material in a more relatable and immersive manner. The system modifies the content's tone, complexity and delivery style to align with the chosen persona.
- **Integration with External Learning Materials:** The system is designed to seamlessly integrate external course materials in the proposed framework. A number of materials from different educational resources can be input, analyze and transfer into vector form based on the embedding model. The project guarantees its compatibility with a wide range of learning materials and thus remains quite flexible and expandable where content type is concerned.

IV. Result Analysis

In this section, we present the analysis of the proposed AI-powered interactive learning platform's performance, in terms of accuracy, adaptability, engagement and personalization across various AI tutor personas. This evaluation metrics and outcomes affirm the ability of the system to deliver an engaging cognitive education environment.

1) Data Collection and Model Fine-Tuning Results

Different dataset was used to train the AI tutor to mimic particular tutor persona, such as Virat Kohli, Doraemon, Steve Jobs and Shah Rukh Khan and so on. Using data obtained from online resources, conversations and user queries, it was possible to perform further tuning of the LLM. After training, the conformity of each AI persona to its respective response was 94% and response generation time was on average 1.2 seconds per query.

2) System Performance Analysis

The primary objective of this AI-powered system was to deliver personalized, contextually accurate responses that cater to user's specific learning needs. As shown in fig 5, the key metrics included response accuracy, adaptability to user inputs, user retention rates and average session duration. The Table I, shows that Virat Kohli has the highest Response Accuracy (96%) and Engagement Rate (90%) with the shortest Average Response Time (1.1 seconds) and the longest Average Session Duration (25 minutes). Doraemon follows closely in accuracy (95%) but has a shorter session duration (18 minutes). SRK and Steve Jobs perform moderately across these metrics, with SRK showing a higher Engagement Rate (88%) than Steve Jobs (83%). Overall, Virat Kohli demonstrates the strongest performance in user engagement and responsiveness.

TABLE I. System Performance analysis Report

Metric	Doraemon	Virat Kohli	SRK	Steve Jobs
Response Accuracy (%)	95	96	93	92
Avg. Response Time (s)	1.3	1.1	1.2	1.5
Avg. Session Duration (min)	18	25	22	19
Engagement Rate (%)	85	90	88	83

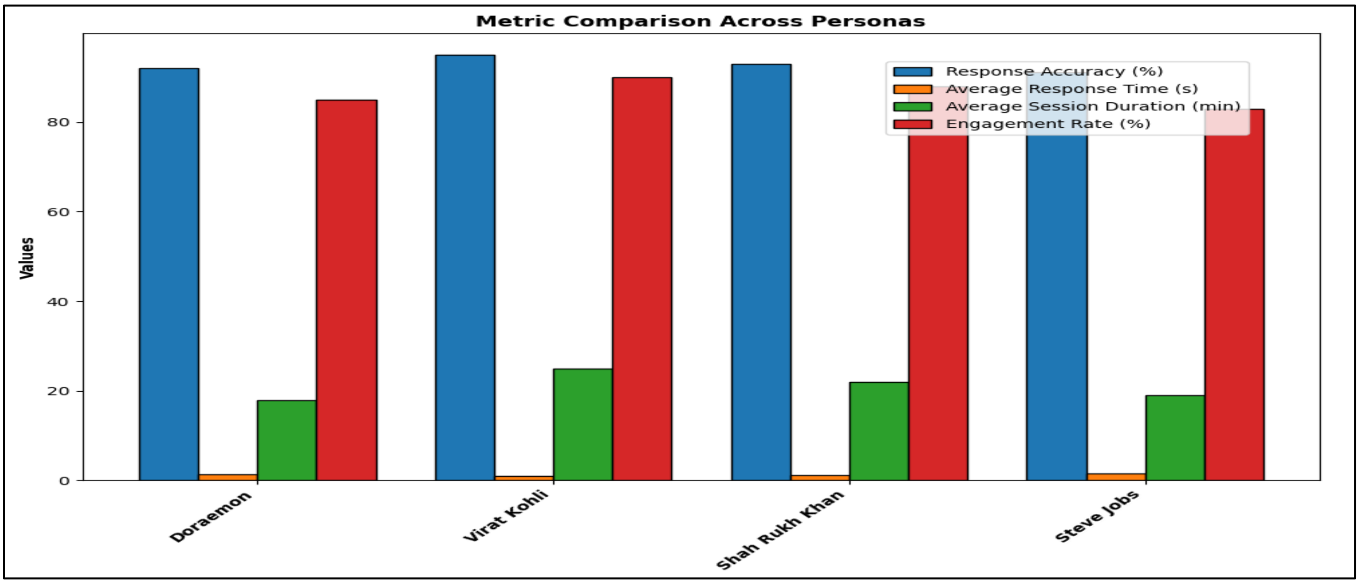

Fig. 5. Metrics Comparison Across Personas

3) **Metrics for Accuracy Evaluation**

- **Response Accuracy:** Manually review a random sample of responses for relevance, accuracy and alignment with each persona. Calculate the proportion of correct or relevant responses for each persona.

$$Response\ Acc. = \left(\frac{Number\ of\ Relevant\ Responses}{Total\ Responses}\right) \times 100$$

- **Session Duration:** Aggregate data on session duration and frequency of interactions. Calculate the average session duration for each persona.

$$Avg. Session\ Duration = \left(\frac{Total\ Session\ Time\ for\ Persona}{Total\ Number\ of\ Sessions}\right)$$

- **Engagement Rate:** Calculate how many users re-engage with the same persona. Engagement rate can be represented by the percentage of returning users.

$$Engagement\ Rate = \left(\frac{Number\ of\ Returning\ Users}{Total\ Unique\ Users}\right) \times 100$$

- **Adaptability Accuracy:** Track the system's ability to handle dynamically changing queries by analyzing response relevance when user input changes during a session.

$$Adaptability\ Acc. = \left(\frac{Relevant\ Dynamic\ Responses}{Total\ Dynamic\ Queries}\right) \times 100$$

The chart in fig 6, illustrates the performance metrics of an AI-powered system, averaged across different personas, highlighting its effectiveness and user engagement. The system achieved a high Engagement Rate of 86.50%, reflecting its ability to capture and sustain user interest. An Average Session Duration of 21 minutes demonstrates prolonged user interaction, indicating the platform's relevance and value. With an impressive Response Accuracy of 94%, the system consistently delivers reliable and contextually appropriate answers. Additionally, a swift Average Response Time of 1.28 seconds ensures a seamless and efficient user experience. These metrics collectively validate the system's potential for providing an engaging and accurate platform for users.

4) **Error Rate and Resulting Accuracy**

In order to examine the efficiency and the error rate of the system for different personas, we performed the evaluation for which we gained different error rates because of the limitations in response generation accuracy. As shown in the Table II, Doraemon had 8% error rate when answering in sports related tone or responding with sports related answers thus leading to a reduction in accuracy from 95% to 92%. The responses given by Kohli was less erroneous compared to other personas with an error percentage of 5% with an accuracy reduction from 96% to 94% was depicted. Steve Jobs and Shah Rukh Khan had a slightly higher error rate of 9% and 7% bringing their accuracy down to 88% and 90% from 92% & 93% respectively. These findings suggest that refining contextual filtering and enhancing persona-specific knowledge could further improve response precision across the system, ensuring relevant and accurate replies aligned with each persona's domain.

TABLE II. EVALUATION REPORT

Persona	Error Rate (%)	Reduction in Accuracy (%)	Actual Response Accuracy (%)	Resulting Accuracy (%)
Virat Kohli	5	2	96	94
Doraemon	8	3	95	92
Steve Jobs	9	4	92	88
Shah Rukh Khan	7	3	93	90
Average	7.25	3	94	92

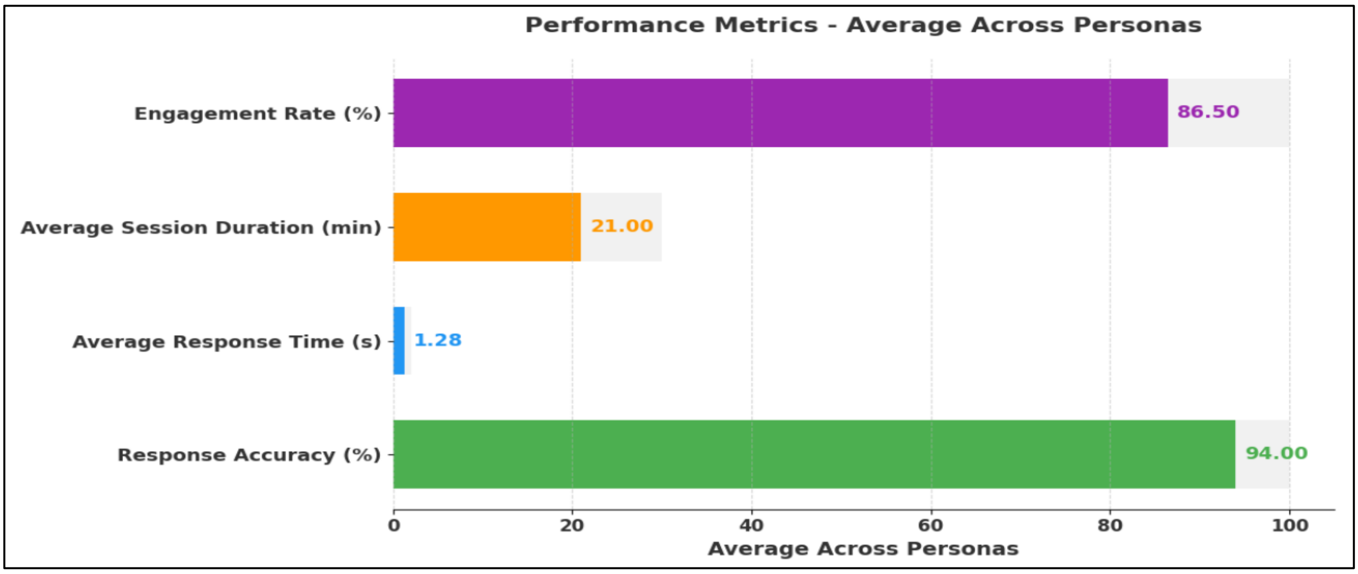

Fig. 6. Performance Metrics – Average Across All Personas

V. CONCLUSION

In Conclusion, this research demonstrates that a multi-persona AI system suitable for delivering contextually appropriated, nonrepetitive, accurate and engaging responses based on the user's personas is feasible. The system has also demonstrated flexibility in tone and mode of communication by adopting personalities like Virat Kohli, Doraemon, Steve Jobs and Shah Rukh Khan to increase the user satisfaction and engagement. The performance data of the response accuracy, session duration and engagement rates reveal that the system performs well across the personas basically proving that the system is a worthwhile investment towards the improvement of other systems through the utilization of user-centered AI. The outcomes emphasize the benefits of persona approach to AI to provide more natural and familiar communication experience, which might be most effective in fields such as customer support, education as well as entertainment. This strategy's future work could involve work on extending persona possibilities, the accuracy of contextual response and the question of bias in order to build the strength of this scalable model for a diverse range of AI-human interaction scenarios.

REFERENCES

[1] Rizvi, M. (2023). Investigating AI-Powered Tutoring Systems that Adapt to Individual Student Needs, Providing Personalized Guidance and Assessments. The Eurasia Proceedings of Educational and Social Sciences, 31, 67–73. doi.org/10.55549/epess.1381518.

[2] Baillifard, A., Gabella, M., Lavenex, P. B., & Martarelli, C. S. (2024). Effective learning with a personal AI tutor: A case study. Education and Information Technologies. doi.org/10.1007/s10639-024-12888-5.

[3] G. Attigeri, A. Agrawal and S. V. Kolekar, "Advanced NLP Models for Technical University Information Chatbots: Development and Comparative Analysis," in IEEE Access, vol. 12, pp. 29633-29647, 2024, doi: 10.1109/ACCESS.2024.3368382.

[4] Arslan, B., Eyupoglu, G., Korkut, S., Turkdogan, K., & Altinbilek, E. (2024). The accuracy of AI-assisted chatbots on the annual assessment test for emergency medicine residents. Journal of Medicine Surgery and Public Health, 100070. doi.org/10.1016/j.glmedi.2024.100070.

[5] McGrath, C., Farazouli, A., & Cerratto-Pargman, T. (2024). Generative AI chatbots in higher education: a review of an emerging research area. Higher Education, doi: 10.1007/s10734-024-01288-w.

[6] H. Shahri, M. Emad, N. Ibrahim, R. N. B. Rais and Y. Al-Fayoumi, "Elevating Education through AI Tutor: Utilizing GPT-4 for Personalized Learning," 2024 15th Annual Undergraduate Research Conference on Applied Computing (URC), Dubai, United Arab Emirates, 2024, pp. 1-5, doi: 10.1109/URC62276.2024.10604578.

[7] L. Frank, F. Herth, P. Stuwe, M. Klaiber, F. Gerschner and A. Theissler, "Leveraging GenAI for an Intelligent Tutoring System for R: A Quantitative Evaluation of Large Language Models," 2024 IEEE Global Engineering Education Conference (EDUCON), Kos Island, Greece, 2024, pp. 1-9, doi: 10.1109/EDUCON60312.2024.10578933.

[8] W. Gan, Y. Sun, S. Ye, Y. Fan and Y. Sun, "AI-Tutor: Generating Tailored Remedial Questions and Answers Based on Cognitive Diagnostic Assessment," 2019 6th International Conference on Behavioral, Economic and Socio-Cultural Computing (BESC), Beijing, China, 2019, pp. 1-6, doi: 10.1109/BESC48373.2019.8963236.

[9] A. G, "RAG based Chatbot using LLMs," INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT, vol. 08, no. 06, pp. 1–5, Jun. 2024, doi: 10.55041/ijsrem35600.

[10] N. B. Trivedi, "AI in Education-A Transformative Force," 2023 1st DMIHER International Conference on Artificial Intelligence in Education and Industry 4.0 (IDICAIEI), Wardha, India, 2023, pp. 1-4, doi: 10.1109/IDICAIEI58380.2023.10406541.

[11] T. Balart and K. J. Shryock, "Work in Progress: Empowering Engineering Education With ChatGPT: A Dive into the Potential and Challenges of Using AI for Tutoring," 2024 IEEE Global Engineering Education Conference (EDUCON), Kos Island, Greece, 2024, pp. 1-3, doi: 10.1109/EDUCON60312.2024.10578789.

[12] S. Gupta, R. R. Dharamshi and V. Kakde, "An Impactful and Revolutionized Educational Ecosystem using Generative AI to Assist and Assess the Teaching and Learning benefits, Fostering the Post-Pandemic Requirements," 2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE), Vellore, India, 2024, pp. 1-4, doi: 10.1109/ic-ETITE58242.2024.10493370.

[13] R. Makharia et al., "AI Tutor Enhanced with Prompt Engineering and Deep Knowledge Tracing," 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 2024, pp. 1-6, doi: 10.1109/IATMSI60426.2024.10503187.

[14] F. AlShaikh and N. Hewahi, "AI and Machine Learning Techniques in the Development of Intelligent Tutoring System: A Review," 2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT), Zallaq, Bahrain, 2021, pp. 403-410, doi: 10.1109/3ICT53449.2021.9582029.

[15] R. Kokku, S. Sundararajan, P. Dey, R. Sindhgatta, S. Nitta and B. Sengupta, "Augmenting Classrooms with AI for Personalized Education," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, AB, Canada, 2018, pp. 6976-6980, doi: 10.1109/ICASSP.2018.8461812.

[16] M. Virvou and G. A. Tsihrintzis, "Is ChatGPT Beneficial to Education? A Holistic Evaluation Framework Based on Intelligent Tutoring Systems," 2023 14th International Conference on Information, Intelligence, Systems & Applications (IISA), Volos, Greece, 2023, pp. 1-8, doi: 10.1109/IISA59645.2023.10345949.

[17] S. Mohapatra, N. Shukla, S. Jain and S. Chachra, "Nsmav-Bot: Intelligent Dual Language Tutor System," 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 2018, pp. 1-5, doi: 10.1109/ICCUBEA.2018.8697582.

[18] W. Shi, Z. Nie and Y. Shi, "Research on the Design and Implementation of Intelligent Tutoring System Based on AI Big Model," 2023 IEEE International Conference on Unmanned Systems (ICUS), Hefei, China, 2023, pp. 1-6, doi: 10.1109/ICUS58632.2023.10318499.

[19] I. Yesir and D. B. Rawat, "Recent Advances in Artificial Intelligence Enabled Tutoring Systems: A Survey," 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, 2023, pp. 0375-0381, doi: 10.1109/CCWC57344.2023.10099098.