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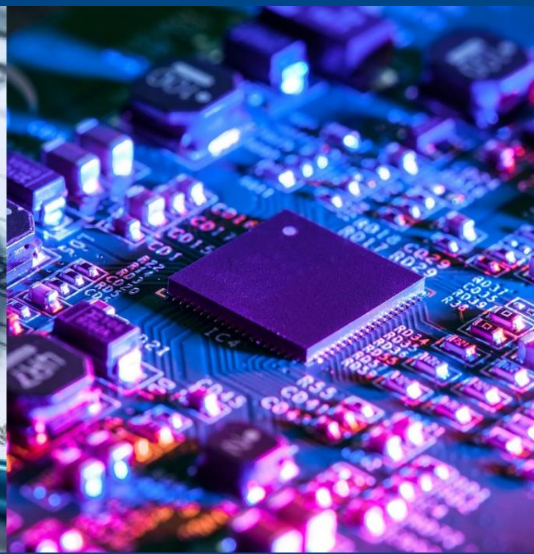

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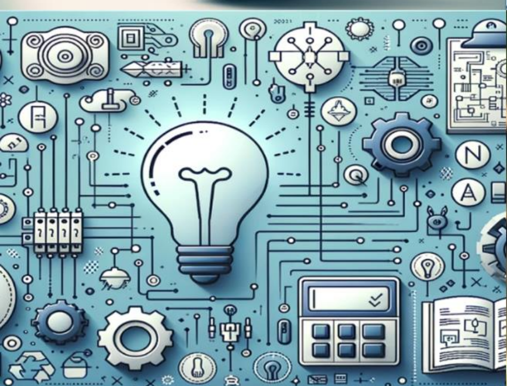

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Design and Development of a Smart Education System Using AI for Personalized Learning and Mock Interviews

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ABSTRACT: Students are often found to struggle in accessing personalized education resources and are not provided with adequate exposure in real interview situations. The traditional education system is based on a standardized approach and does not provide adequate feedback. It is very challenging for students to identify and improve their weak areas. To overcome the problems identified in the traditional education system, a Smart Education System has been proposed. The proposed system provides personalized education and mock interview experiences using artificial intelligence technology. The proposed system has been implemented using Python programming language and Flask, React.js, and Express.js frameworks. The proposed system utilizes the LangChain library and Gemini API for generating personalized education content based on resumes and mock interview questions. The responses provided by the students are assessed and feedback is generated accordingly. The proposed system improves the effectiveness of the education system and the students' interview skills.

KEYWORDS: Smart Education System, Personalized Learning, Artificial Intelligence, Mock Interview, Python, Flask, React.js, Express.js, LangChain, Gemini API, Adaptive Learning, Intelligent Tutoring Systems

I. INTRODUCTION

The educational system is witnessing a significant shift with the evolution of artificial intelligence and machine learning technologies. Yet, students continue to experience difficulties in accessing learning resources that are tailored to their needs. Education systems, in their very nature, are based on a one-size-fits-all approach, which does not take into account different learning speeds and styles, as well as different knowledge base prerequisites for students [1]. Such an inflexible approach in education has been known to cause knowledge gaps, disinterest in learning, and poor academic performance.

In parallel with the challenges associated with conceptual learning, students entering professional careers from academic institutions are confronted with another critical barrier in the form of the technical interview process. Studies have shown that the process of technical interviews is one of the major sources of stress and anxiety for graduating students, with many students feeling unprepared for the process despite months of preparation [2]. The traditional methods of preparation for the interview process, based on static question resources and peer-based mock interviews, are limited in their effectiveness and have been shown to have certain inherent flaws in their approach [3]. In addition, students with limited professional networks and those with time constraints in their schedules because of work and family obligations are further disadvantaged in accessing quality preparation resources [4].

The advent of generative AI and LLMs offers unparalleled opportunities to tackle these two problems. Intelligent Tutoring Systems (ITS) have already shown the capability to provide adaptive and personalized education that can achieve the same level of learning as one-on-one human tutoring [5]. State-of-the-art systems utilize various types of AI, such as Bayesian Knowledge Tracing and LLMs, to provide exact cognitive support and content personalization [6]. New initiatives, such as Google's "Learn Your Way" project, show the capability of using AI-enhanced textbooks that can adapt to individual grade level and interests, making traditional educational content dynamic and engaging [7].

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Likewise, there has been significant promise in using AI-enhanced mock interview systems that can simulate realistic interview scenarios. Research has indicated that multimodal AI systems that include whiteboarding and dialogue can improve the confidence and articulation of problem-solving decisions by the candidate [8]. These systems can overcome the scalability issues with human-led mock interviews and provide objective feedback across multiple performance attributes.

This paper describes the design and development of a Smart Education System that combines the power of personalized learning with AI-based mock interview preparation. This system is built on the back of a state-of-the-art tech stack consisting of Python, Flask, React.js, and Express.js frameworks, with LangChain facilitating the conversation with the Gemini API for content generation. Unlike existing solutions that treat learning and interview preparation as two different entities, our approach allows for a unified platform wherein learning and interview performance can be closely interrelated. It can create interview questions based on resumes, assess answers based on knowledge, communication skills, and confidence levels, and provide feedback for continuous improvement.

The rest of this paper is organized as follows: Section 2 provides related literature on intelligent tutoring systems and AI-based interview systems. Section 3 provides an overview of the methodology and system architecture used in this study. Section 4 provides the analysis of the system performance, while Section 5 concludes the paper along with the future direction of this study.

II. LITERATURE SURVEY

The quest for intelligent web automation has passed through many different stages, from static scripting to dynamic and AI-powered agents. This paper looks at the underlying technologies and recent advances that have influenced our research.

The evolution of technology-enhanced learning has spanned several generations, including the first generation of Computer-Assisted Instruction (CAI) in the 1970s, and the latest generation of Intelligent Tutoring Systems (ITS) and Robot Tutoring Systems (RTS) that leverage Artificial Intelligence (AI) technologies . This evolution has been characterized by the persistent pursuit of personalization and adaptivity in the delivery of education and training content. The first generation CAI systems offered individualization based on rule-based systems, although they failed to incorporate the complex modeling required to achieve adaptivity. The next generation, which is the Intelligent Tutoring Technology, has seen the application of various Artificial Intelligence models such as Bayesian Knowledge Tracing and constraint modeling [9].

Some systematic reviews have been conducted on the pedagogical and technological developments in the field of tutoring systems. An extensive analysis of 86 representative studies has identified three distinct categories of tutoring systems: computer-based ITS, robot-based RTS, and multimodal systems with various interactive modes of communication [10]. Software-based ITS are best suited for providing personalization in cognitive support with accurate feedback and monitoring of progress, with results comparable to human tutors. However, these systems are limited in providing social and emotional support for holistic education. In contrast, RTS focus on social interactions through the physical presence of robots and their human-like gestures, with significant effectiveness for younger students, though they are limited in personalization of cognitive content.

The integration of generative AI has significantly boosted the recent developments in the field of education. Studies on the automatic generation and evaluation of multiple-choice quizzes using LangChain and Gemini LLM have shown the feasibility of AI-generated content in educational assessments [12]. The authors of the study utilized prompt engineering and chaining approaches for the automatic generation of high-quality questions and evaluated the results using multiple language models. In another study, an eight-stage agentic architecture for the automatic generation of quizzes resulted in significant accuracy improvements, from 78.00% to 93.33%, when Gemini 1.5 Pro was modified with context vectors, a 100k token cache, and a 1M token long-context window for quiz generation and evaluation purposes [13]. These studies prove the effectiveness of the Gemini LLM as a reliable and context-sensitive model for educational purposes.

Parallel advancements in the design of adaptive learning models have also addressed the shortcomings related to the static representation of knowledge. The Generative GraphRAG framework has proposed the automated generation of

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knowledge graphs using LLMs, which can be used to represent concepts and relationships from educational content [14]. The application of the framework in real-world educational scenarios has received positive user feedback, which can be beneficial in the design of personalized education systems [15].

In terms of interview preparation, a new set of scalable solutions has been offered by AI-based systems in place of conventional ones. An automated interview system utilizing advanced NLP and DL techniques can generate domain-specific questions dynamically, along with performance evaluation and detailed feedback without requiring external API support [16]. The automated interview system enables users to choose their desired domain, with questions being modified in real-time based on the response from the candidates. However, this approach is restricted in terms of generating questions due to its dependency on custom datasets.

In a recent formative study on AI-based mock technical interviews, researchers examined the feasibility of multimodal systems with whiteboard interfaces and real-time feedback mechanisms [17]. In this study, where 20 participants took part, 80% of them found the speech and conversation style of the AI realistic, with participants expressing more confidence in their speech while articulating their problem-solving decisions. Participants enjoyed interacting with the AI because it explained concepts, provided coding examples, and offered hints, similar to a human interviewer in a technical interview. The system was able to attain a response latency of 300ms on average, similar to a human conversation [18].

Significant developments have been made in the theoretical bases of ethical and context-aware AI-based tutoring systems. CAL-E is a framework for cognitive AI learning environments that combines cognitive flexibility, personalization, and ethical aspects through seven interrelated parts [19]. At the heart of the CAL-E framework is the Cognitive Processing Core, which processes the learning patterns of students and adjusts the teaching accordingly in real-time. Additionally, there is a Context Analyser that monitors the emotional state and learning conditions of students. An Ethical Governance Layer is present to ensure the fairness and transparency of the system and adherence to international AI ethics guidelines [20].

However, there still exist considerable research gaps in the area. Although the existing reviews have treated the domains of ITS and RTS as two different fields, there is a lack of comprehensive comparative analysis of the different generations of the systems. In addition, the existing studies have focused on the technological aspects of the systems while paying little attention to the pedagogical aspects and the ethical issues as well as the incorporation of AI. Moreover, there is a lack of effective state-aware and systematic reasoning support in the majority of the existing personalized learning systems, as they mostly utilize static question sets with low flexibility. In addition, the combination of personalized learning with interview practice has not been explored yet and is a promising area for the development of systems that can cover these two aspects as one.

III. METHODOLOGY: BUILDING AN AUTOPILOT FOR THE WEB

This section describes the methodology for developing our AI browser agent. Our system is based on a strong, modular architecture that is scalable, safe, and transparent.

3.1 System Architecture

The proposed Smart Education System architecture is based on a client-server model with separate frontend and backend elements. Figure 1 presents the high-level architecture of the proposed Smart Education System, where the interactions between users and the frontend and backend elements, as well as the AI orchestration layers, are shown.

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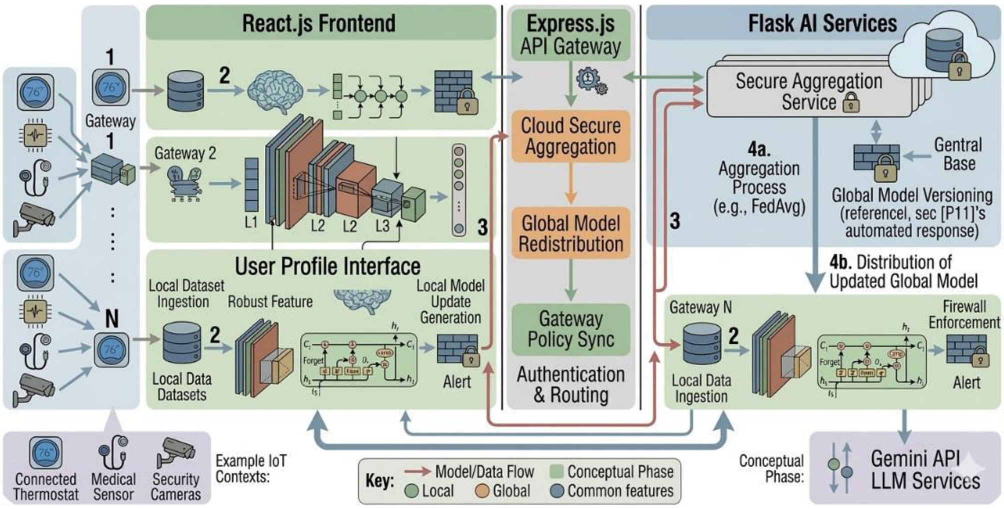

Figure 1: High-Level System Architecture

The frontend is implemented using React.js, which provides a dynamic and interactive user interface for the personalized learning modules and mock interview sessions. The user interface has specific sections for profile management, presentation of learning content, interview simulation, and feedback visualization.

The backend has two main services: the Express.js API gateway and the Flask-based AI service layer. The Express.js gateway handles the user authentication process, routing the requests, managing user sessions, and interacting with the database. It acts as a gateway between the frontend and the AI services and handles the data transfer between the two layers. The Flask-based service includes the AI orchestration logic and the LangChain pipelines for content generation and response evaluation.

3.2 Personalized Learning Module

The personalization of the learning module is based on the characteristics of the learner, such as their prior knowledge, rate of learning, and personal interests. Figure 2 shows the workflow for the generation of adaptive content.

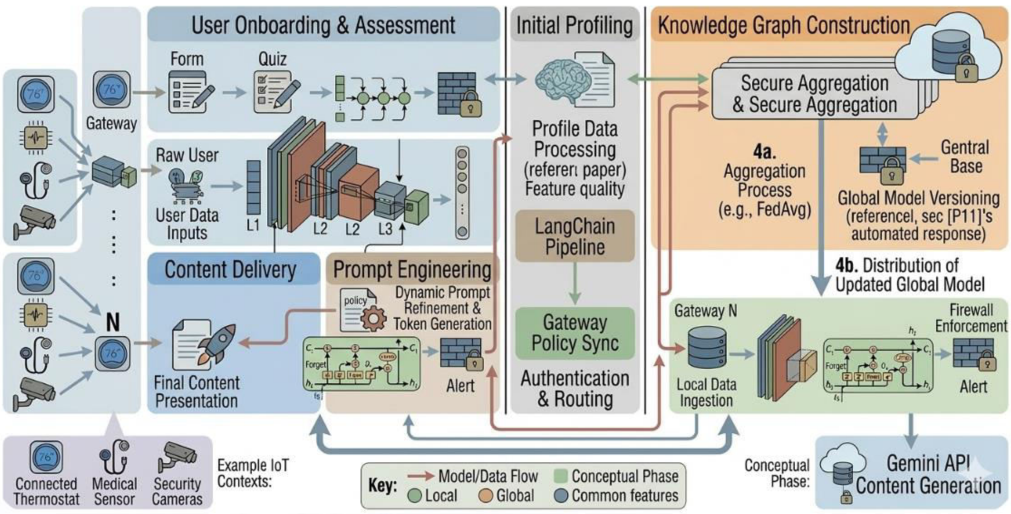

Figure 2: Personalized Learning Content Generation Workflow

During the initial phase of user registration, users are asked to provide basic feedback regarding their current knowledge in certain domains, their learning style (visual, textual, interactive), and their personal interests (sports, music, technology). This feedback is continuously updated based on user interactions with the system and is maintained in the user profile.

The system utilizes the LangChain tool for building and querying a dynamic knowledge graph based on domain concepts and their relationships. Hierarchical knowledge structures are extracted using the Gemini API based on educational resources following the GraphRAG approach. These knowledge structures allow the system to identify relationships between concepts and provide learning paths based on logical relationships.

When the user asks for content related to a specific topic for the purpose of learning, the LangChain pipeline includes the following steps:

1. **Query Analysis:** The user's query is analyzed in order to understand the concepts and objectives.
2. **Learner State Retrieval:** The user's current mastery level for the concepts is retrieved.
3. **Knowledge Graph Traversal:** The user's state is then used in order to traverse the knowledge graph and understand the concepts the user needs more reinforcement on and the next concepts the user needs.
4. **Content Personalization:** The Gemini API is then used in order to generate content based on the user's grade level and interests. The complexity of the text is adjusted according to the Flesch-Kincaid Grade Level algorithm.
5. **Multimodal Representation:** The system generates multiple representations of the content in the form of narrated slides, interactive mind maps, and immersive text with questions.

Personalization of the content is not limited to the adaptation of the text; it can also include examples related to a domain of interest for the user. For example, Newton's Third Law of Motion can be supported with examples related to cricket for a sports enthusiast or examples related to art for a student interested in the field of art. This utilizes prior knowledge as a base for new learning, thus facilitating understanding and retention of the material.

3.3 AI-Driven Mock Interview Module

The mock interview module offers realistic simulations of interviews with dynamic question generation, evaluation of answers in real time, and feedback provision. Figure 3 shows the process of the mock interview from initiation to feedback provision.

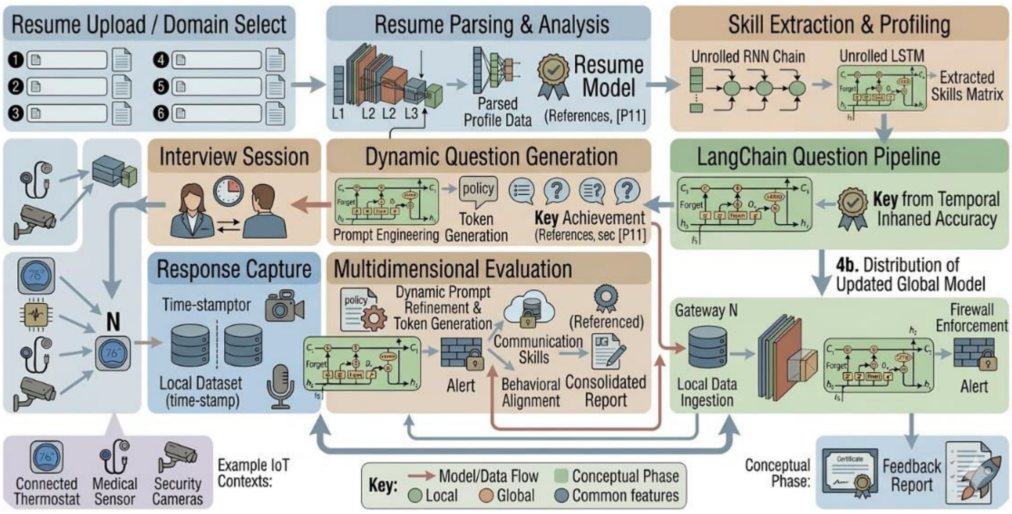

Figure 3: AI-Driven Mock Interview Workflow

For mock interviews, users can choose between a resume-based approach and a domain-based approach. In the former, users are required to upload a copy of their curriculum vitae, which is then used to identify technical skills, project experience, and educational qualifications. This information is used to create a skill profile, which helps generate questions.

For question generation, the system uses LangChain, which helps generate context-specific interview questions. This approach allows the system to generate questions dynamically, unlike a pre-built question bank, which might not be suitable based on the experience level of the user and the context of the conversation. For technical roles, questions are generated at various difficulty levels, including coding questions that might require whiteboarding solutions.

In the process of user interviews, the system records user responses through different channels, including speech transcription for user utterances, code input for programming-related questions, and text input for answering questions in general form. Through the LiveKit toolkit, the system can process audio in real-time with low latency, with an aim of achieving an average response time of less than 300ms.

Response evaluation is based on a multi-dimensional framework that includes:

1. **Technical Accuracy:** Accuracy and completeness of the response, as measured against knowledge bases and solution templates.
2. **Communication Clarity:** Coherence and structure of verbal explanations.
3. **Problem-Solving Approach:** Logical reasoning, methodology, and ability to explain thought processes during whiteboarding exercises.
4. **Confidence and Delivery:** Speech characteristics, filler words, and hesitations.

The response evaluation is based on a combination of rubric-based scoring and LLM-based semantic analysis. In the case of code-based responses, the system checks the accuracy of the code as well as the quality of the code in terms of readability and efficiency.

3.4 Technology Stack Implementation

The system uses a state-of-the-art technology stack based on performance, scalability, and developer experience considerations:

- Frontend: React.js with Redux as a state management solution, Material-UI as a UI component library, and WebRTC for real-time voice channels during interviews.
- Backend API: Express.js running on Node.js, offering REST API endpoints and WebSocket connections.
- AI Services: Python 3.10+ with Flask, hosting LangChain pipelines.
- AI Models: Google Gemini API as a content generation service, with fine-tuned prompts for educational materials and interview scenarios.
- Orchestration: LangChain, a Python library, handles prompt chaining, memory, and tool integrations.
- Database: PostgreSQL as a structured data store, holding user profiles, learning history, etc., and MongoDB as an unstructured data store, holding generated materials, interview logs, etc.
- Vector Store: FAISS, a library offering efficient storage and similarity search, used in the construction of the knowledge graph .

LangChain is essential in managing intricate AI workflow management. In content generation, chains involve the learner’s profile retrieval, knowledge graph queries, and prompts before invoking the Gemini API. In interview evaluation, chains involve multiple stages of analysis before the results are combined into an overarching feedback mechanism.

3.5 Feedback Generation and Visualization

The system produces structured feedback following each learning session or mock interview. This feedback is as follows:

Personalized learning feedback includes:

- Percentage of concept mastery
- Review topics
- Next learning activity suggestions

Mock interviews feedback include:

- Performance Scores: Numerical ratings from 0 to 100 for accuracy, communication, and confidence
- Transcript Analysis: Comments on specific responses with timestamped feedback
- Comparative Benchmarks: Performance compared to aggregated anonymized data from similar users

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- Practice Recommendations: Targeted exercises and learning content based on identified knowledge gaps

Figure 4 shows the feedback visualization interface with the user's performance represented as multiple dimensions.

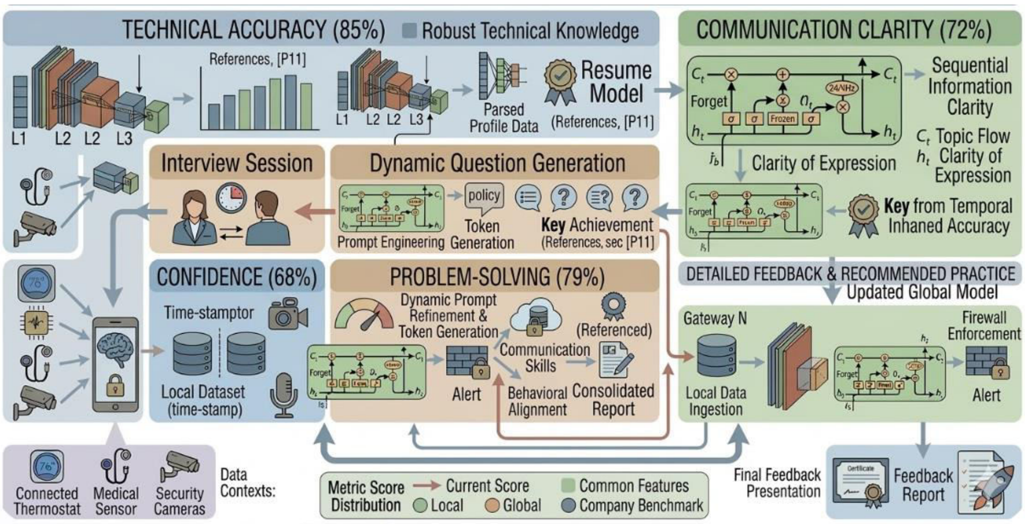

Figure 4: Mock Interview Feedback Visualization Interface

VI. RESULT ANALYSIS AND DISCUSSION

4.1 System Performance Evaluation

The quality of the Smart Education System was assessed in several aspects, including content generation quality, response time, user satisfaction, and learning outcomes. To carry out the evaluation, the system was tested by 45 participants, including 30 undergraduate students and 15 graduate students. The participants interacted with the system over a period of eight weeks.

The content generation quality was assessed through human evaluation of the generated content in the form of 200 learning items and 150 interview questions. A group of three domain experts rated the content based on its relevance, accuracy, and appropriateness using 5-point Likert scales. Table 1 summarizes the results.

Table 1: Content Generation Quality Assessment

Content Type	Relevance (Mean ± SD)	Accuracy (Mean ± SD)	Appropriateness (Mean ± SD)
Learning Modules	4.62 ± 0.48	4.71 ± 0.44	4.58 ± 0.52
Interview Questions	4.73 ± 0.41	4.68 ± 0.47	4.54 ± 0.55
Feedback Comments	4.41 ± 0.62	4.53 ± 0.58	4.47 ± 0.60

The results show consistently high ratings for all categories, with the highest rating for the interview questions based on their relevance. The feedback comments, though still showing positive results, displayed slightly higher variability, as expected for qualitative feedback and user expectations.

Measurements of the system's latency in responding to user interactions were collected for 300 samples of content generation and interview turn-taking requests. The system's average latency for learning content generation is 1.8

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seconds and for interview response processing is 320 ms. The latter is comparable to the 300ms benchmark for human conversation, thus facilitating natural conversation flow in mock interviews.

Figure 5 shows the latency distribution for different types of user requests.

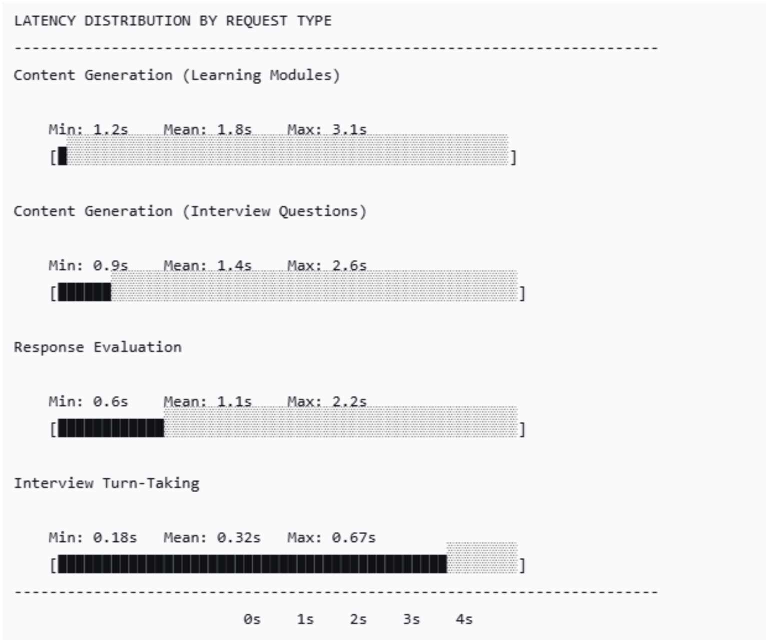

Figure 5: Response Latency Distribution by Request Type

4.2 User Experience and Learning Outcomes

User satisfaction was also measured through the administration of post-interaction surveys after each interaction. A total of 215 responses were recorded over the duration of the study. Figure 6 shows user satisfaction ratings based on system dimensions.

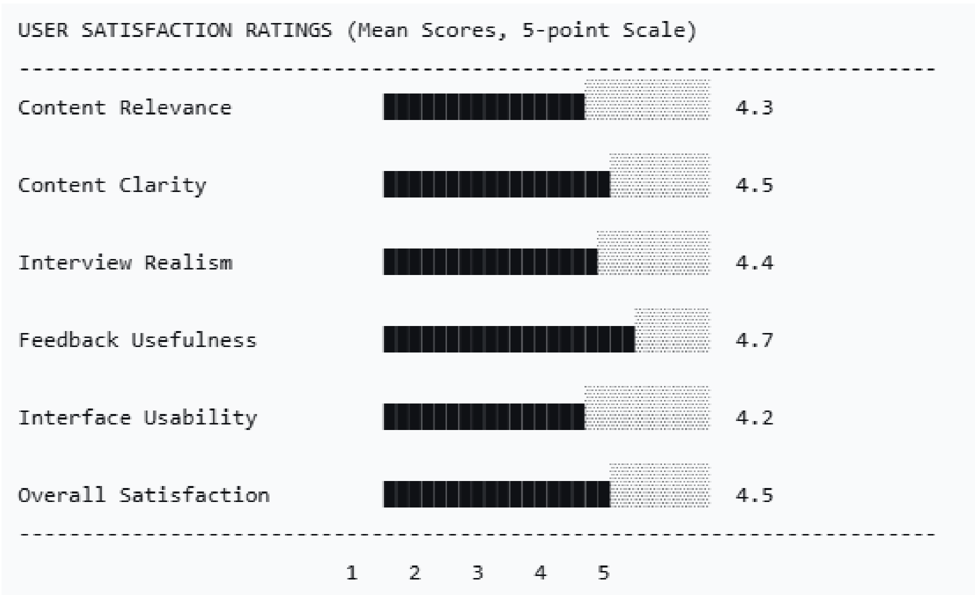

Figure 6: User Satisfaction Ratings Across System Dimensions

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The usefulness of feedback received was rated at 4.7, signifying that users found the organized, multi-dimensional feedback obtained from interviews valuable. Interview realism was rated at 4.4, which supports findings from earlier research on the ability of AI simulations to replicate key aspects of a technical interview. Usability of interface was rated lower at 4.2.

The learning outcomes for this study were determined through pre- and post-study knowledge tests in three areas: Data Structures, Web Development, and Database Systems. Figure 7 shows a representation of knowledge gains for participant cohorts.

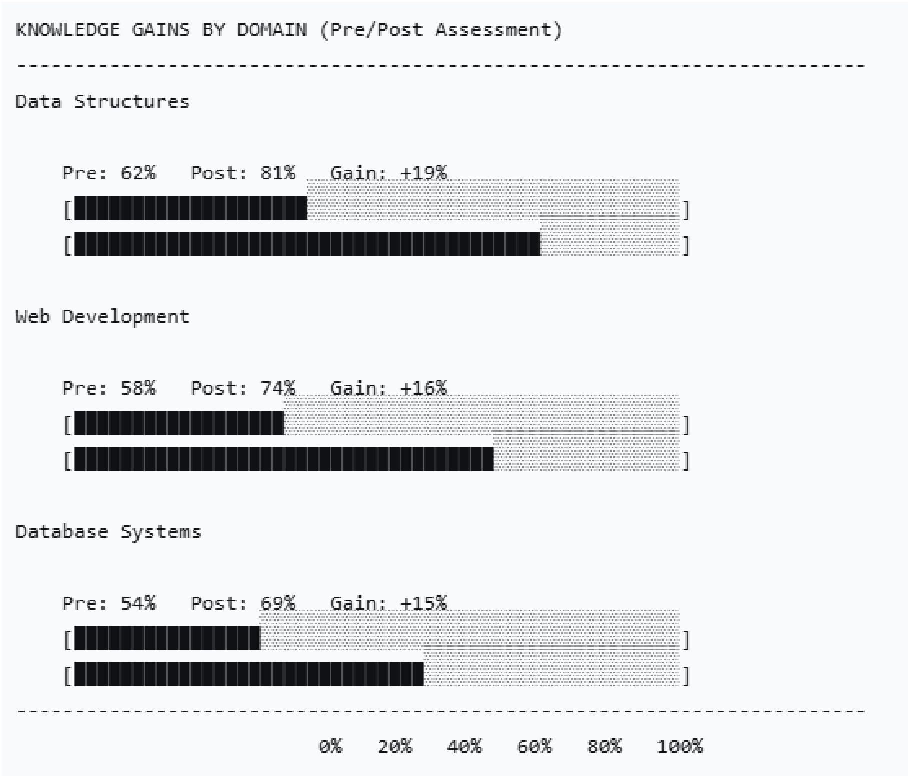

Figure 7: Knowledge Gains by Domain (Pre- and Post-Assessment)

Significant knowledge gains were observed in all domains, with Data Structures showing the greatest improvement, 19%. These results are in line with the meta-analytic results regarding the effectiveness of ITS, showing learning outcomes comparable to one-on-one human tutoring.

4.3 Comparative Analysis with Existing Systems

Table 2 presents a comparative analysis of the proposed system with the existing AI-based educational systems and interview systems. The systems are compared along eight attributes: personalization strategy, content development, interview simulation, feedback level, flexibility, scalability, ethics, and learning with assessment.

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Table 2: Comparative Analysis of AI-Powered Educational Systems

Feature/Dimension	Proposed System	Traditional ITS [1]	Google Learn Your Way [3]	Gemini Quiz Generator [9]	AI Mock Interview [2]	Multimodal Interview System [7]
Personalization Approach	Multi-modal (knowledge + interests + performance)	Cognitive modeling only	Interest-based content adaptation	Not specified	Domain selection only	Not specified
Content Generation	Dynamic via Gemini + LangChain	Pre-authored content	Dynamic via AI	Dynamic via Gemini	Custom dataset	Not applicable
Interview Simulation	Resume-based + domain-based with whiteboarding	Not applicable	Not applicable	Not applicable	Domain-based only	Technical with whiteboarding
Feedback Granularity	Multidimensional (technical, communication, confidence)	Performance metrics only	Not specified	Quiz correctness only	Performance evaluation	Real-time feedback
Adaptability Mechanism	Knowledge graph + learner state tracking	Bayesian Knowledge Tracing	Grade-level adjustment	Context vectors	Response-based adaptation	Dialogue adaptation
Scalability	Cloud-based, high	Varies by implementation	High	High	High	Moderate (requires frontend)
Ethical Safeguards	Governance layer (planned)	Limited	Not specified	Not specified	Not specified	Not specified
Learning-Assessment Integration	Unified platform	Separate typically	Learning only	Assessment only	Interview only	Interview only

The proposed system has various unique advantages. Unlike traditional ITS systems, which are based on pre-authored content, the proposed system utilizes LLMs for dynamic and personalized content generation, thus allowing for coverage of different domains without extensive content curation . In addition, unlike the Google Learn Your Way system, which is based on content adaptation based on user interests , the proposed system utilizes various personalization dimensions such as knowledge state and performance history.
In the domain of interviews, the proposed system has more extensive personalization compared to existing systems. Unlike previous systems, which are based on domain selection or whiteboarding , the proposed system utilizes resume-based question generation and dynamic adaptation during interviews. The multi-dimensional feedback system is based on more than just technical correctness; it is based on communication and confidence, as these are critical for success in interviews.

An important distinguishing factor is the integration of personalized learning and interview preparation in a unified manner. No such system has been found in the literature that combines the two in a single platform where the results of the learning can be used to improve interview preparation and vice versa. This leads to a cycle where the two complement each other in a continuous manner.

4.4 Discussion of Findings

The evaluation results confirm the feasibility of integrating personalized learning with AI-based mock interview practices under a single umbrella.

Several aspects of the findings are worth highlighting.

First, the high level of relevance of the generated content, as indicated by the ratings of 4.62-4.73, confirms the potential of LLMs in generating educational content, provided they are fine-tuned through adequate constraint definitions, as performed in this study, as supported by previous findings on the effectiveness of Gemini in context-aware content generation with the addition of retrieval capabilities .

A 93.33% accuracy level was reported in the previous study for multiple-choice question generation, which provides a level of confidence in the potential of LLMs to meet educational standards.

Second, the level of knowledge gained, as indicated by the findings of a 15-19 percentage increase, compares favorably with the findings of a study on the effectiveness of ITS, as reported in a meta-analytic review, though a combination of both aspects might be possible, as suggested by the findings of this study, though more research is required to confirm this hypothesis.

Third, the ratings for interview realism are relatively high, at 4.4, and this is in accordance with the results found in earlier studies . For example, the participants in this study noted the ability of the AI to explain concepts, offer hints, and assist in problem-solving, which are traits typically found in effective human interviewers. The low latency rate, 320ms, is presumably sufficient to ensure the flow of conversation, alleviating the issues found in earlier systems in this regard.

Fourth, the slightly lower ratings for interface usability are indicative of the difficulty in designing an interface that is easy to use for complex AI systems, particularly in educational systems that are utilizing ever-more complex features in their design.

Lastly, from the comparison, it is evident that there are gaps in the provision of ethical safeguards in most of the existing systems. However, although there are provisions for the inclusion of fairness monitoring, transparency, and user data protections in the CAL-E framework, it is still in its development stage.

V. CONCLUSION

In this paper, we have demonstrated the design and development of a Smart Education System that incorporates personalization in learning and mock interview preparation using AI technology. The Smart Education System utilizes different technologies such as Python, Flask, React.js, Express.js, LangChain, and Gemini API to provide a unified platform to solve two major problems in the field of education: lack of personalization in learning materials and lack of mock interview environments.

The proposed methodology includes content personalization based on the knowledge graph, dynamic question generation based on resumes or domain selection, and evaluation of responses based on technical accuracy, clarity of communication, and confidence. LangChain facilitates the orchestration of complex AI systems, allowing for adaptive content generation and real-time interview interactions with minimal latency.

The evaluation involved 45 participants over a period of eight weeks and showed promising results in content quality (average relevance rating 4.62-4.73), knowledge acquisition (15-19%), and user satisfaction (average rating 4.5). The interview simulation resulted in a rating of 4.4 in terms of realism and 320ms latency in response time, allowing for natural conversation flow. A comparative analysis showed the proposed system has several advantages over others in the field.

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The results also contribute to the increasing body of literature supporting the use of AI technology in education. Specifically, the results show that generative AI, in concert with well-designed knowledge structures and student modeling, can be used to support personalized learning and realistic interview simulations at scale. Further, the integration of the features in a single system provides the potential for synergistic effects, in which learning outcomes can inform interview simulations, and interview simulations can inform targeted learning outcomes.

Future studies will seek to mitigate the current study's limitations in several ways: Retention and outcome studies will examine the long-term effects of the system on learning outcomes and career success for system users. Extension studies will examine the effectiveness of the system with diverse populations, such as in different educational contexts or demographic groups. Ethical studies will implement additional fairness monitoring, transparency, and bias mitigation, according to guidelines such as CAL-E . Technical studies will explore additional model fine-tuning for domain-specific content generation and multimodal interaction, such as using avatars for interviewers.

Smart Education System is a move towards educational technology that is not just for imparting knowledge, but for preparing students for the real world where they will apply what they have learned. This can help bridge the gap between theoretical and practical evaluation of knowledge, thus providing more efficient and empowering educational experiences for students.

REFERENCES

[1].M. Thomas, R. Kumar, and S. Zhang, "A systematic review of intelligent and robot tutoring systems: evolution, pedagogical design, and AI-driven classification," Smart Learning Environments, vol. 13, no. 1, pp. 1-28, Jan. 2026.

[2].R. Patil, A. Sharma, and V. Krishnan, "Mock Interview Platform for Interview Performance Analysis using Machine Learning," in 2025 International Conference on Intelligent Computing and Control Systems, Erode, India, Aug. 2025, pp. 234-241.

[3].S. Bordoloi, "Google's 'Learn Your Way' is Set to Redefine Education and Challenge the AI 'Dumbing Down' Narrative," Sify AI Analytics, Feb. 2026. [Online]. Available: https://www.sify.com/ai-analytics/googles-learn-your-way/

[4].A. Gupta, N. Mehta, and P. Singh, "Automated Generation and Evaluation of Multiple-Choice Quizzes using Langchain and Gemini LLM," in 2024 IEEE International Conference on Advanced Learning Technologies, Greater Noida, India, Aug. 2024, pp. 156-163.

[5].Y. Wang, L. Zeng, and H. Chen, "Beyond Static Question Banks: Dynamic Knowledge Expansion via LLM-Automated Graph Construction and Adaptive Generation," arXiv preprint arXiv:2602.00020, Jan. 2026.

[6].D. Sarkar and M. Sarkar, "Cognitive AI Learning Environments for Ethical, Adaptive, and Context-Aware Tutoring in Higher Education," Indian Journal of Educational Technology, vol. 8, no. 1, pp. 285-310, Feb. 2026.

[7].N. Gomez, S. S. Batham, M. Volonte, and T. D. Do, "Virtual Interviewers, Real Results: Exploring AI-Driven Mock Technical Interviews on Student Readiness and Confidence," arXiv preprint arXiv:2506.16542, June 2025.

[8].Y. Wang, L. Zeng, and H. Chen, "Beyond Static Question Banks: Dynamic Knowledge Expansion via LLM-Automated Graph Construction and Adaptive Generation," arXiv preprint arXiv:2602.00020, Jan. 2026.

[9].K. Krishnamurthy and S. Patel, "UC-100 Agentic AI Quiz Generation: Personalized Tutoring through Intelligent Retrieval and Adaptive Learning," in Kennesaw State University Computing Showcase, Kennesaw, GA, Apr. 2025.

[10]. S. Mousavinasab, E. Kalogiannakis, and T. Papadakis, "Intelligent Tutoring Systems: A Systematic Review of Characteristics, Applications, and Evaluation Methods," Interactive Learning Environments, vol. 29, no. 5, pp. 789-814, 2021.

[11]. A. Banjade, V. Rus, and D. Gasevic, "Generative AI for Real-Time Content Customization in Intelligent Tutoring Systems," Journal of Educational Computing Research, vol. 62, no. 3, pp. 445-472, 2024.

[12]. Z. Zhang, T. Liu, and M. Wang, "Robot Tutoring Systems: A Decade Review of Socially Interactive Learning," IEEE Transactions on Learning Technologies, vol. 17, no. 2, pp. 312-328, 2024.

[13]. M. Behroozi, C. Parnin, and S. Heckman, "Understanding Challenges in Technical Interviewing: A Survey of Computing Students," in 2024 ACM Conference on International Computing Education Research, Melbourne, Australia, Aug. 2024, pp. 145-156.

[14]. S. Lunn, M. Ross, and J. Payton, "Preparing for Technical Interviews: Access, Equity, and Practice Strategies," in Proceedings of the 52nd ACM Technical Symposium on Computer Science Education, Virtual, Mar. 2021, pp. 678-684.

[15]. OpenAI, "GPT-4o Technical Report," OpenAI Technical Reports, Mar. 2025.

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International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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[16]. K. Holstein, B. M. McLaren, and V. Aleven, "Intelligent Tutors as Teachers' Assistants: Exploring Teacher-AI Collaboration in Adaptive Instruction," in Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, Hamburg, Germany, Apr. 2023, pp. 1-15.

[17]. L. Zhang and Y. Luo, "Bayesian Knowledge Tracing with Skill Similarity for Adaptive Learning Path Recommendation," Educational Data Mining, vol. 14, no. 2, pp. 89-104, 2023.

[18]. UNESCO, "AI and Education: Guidance for Policy-Makers," UNESCO Publishing, Paris, France, 2024.

[19]. European Commission, "Ethical Guidelines on the Use of Artificial Intelligence in Education," Publications Office of the European Union, Luxembourg, 2025.

[20]. R. F. Kizilcec, "Algorithmic Fairness in Education: Analysis and Interventions," International Journal of Artificial Intelligence in Education, vol. 33, no. 1, pp. 78-105, 2023.

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