PREPMASTER AN INTELLIGENT SYSTEM FOR TAILORED INTERVIEW TRAINING THE 2D INTERVIEW PANEL

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Dissertation submitted in partial fulfilment of the requirements for the Bachelor of Science (Hons) in Information Technology Specialized in Information Technology

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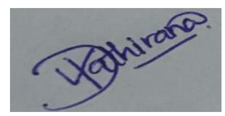
DECLARATION

I declare that this is my own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Name	Student ID	Signature
PATHIRANA V.P.E.P.V.	IT21175084	

Signature of the Supervisor Date

Harshanath S.M.B. 4/11/2025

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ABSTRACT

This research introduce next generation AI powerd 2D Interview panel simulation system Intended to modernize and improve how people prepare for professional job interviews. This system address the constraints of traditional mock interviews by providing a scalable , adaptive , and immersive platform that simulates real world interview dynamics using interactive 2D avatars and Natural Language comprehension. At the heart of the system is an integrated Natural Language Processing (NLP) framework that employs cosine similarity , BERT based Sementic Analysis , and the TF-IDF Vectorization . These strategies work together to determine the sementic significance and clarity of user comments . This enables not only keywords alignment but also a more in depth contextual comprehension and feedback. The technology adapts question complexity in real time , tailoring the interview experience acros three defficulty tiers , Beginners , intermediate , and expert , which are determined by the user's performance advancement.

One of this research's innovative contributions is the use of a two-way interactive method in which the 2D avatars not only pose questions but also answer queries initiated by the candidates. This bidirectional conversation simulates a genuine and spontaneous interview situation , encouraging deeper participation and preparing applicants to handle both scheduled and unstructured dialogue. It also promotes curiosity , active listening and conversational flow all of which are essential abilities in real world interviews. The platform provides domain specific simulation for software engineers , quality assurance engineers , and project managers , with question banks suited to each function. Furthermore , the system incorporates a real time scoring engine that combines syntactic and semantic assessments to provide extensive feedback , performance tracking , and targeted improvement recommendation. Preliminary results show that the system achieves high accuracy in semantic similarity scoring , maintains acceptable latency for real-time interaction, and dramatically enhances user confidence and answer quality throughout repeated sessions. User feedback emphasizes the system's effectiveness in improving soft skills , adaptable thinking and interview readiness.

This research improves AI-based simulation training, intelligent education systems, and career readiness platforms by providing a flexible, intelligent and user-centric approach to interview preparation. It paves the way for broader integration of NLP and interactive AI in educational and professional development tools.

ACKNOWLEDGEMENT

First and foremost, I would like to express my deepest gratitude to my supervisor Mr.Harshanath for the continuous guidance, encouragement, and valuable feedback provided throughout the duration of this research. Your insights were instrumental in shaping the direction of my work and pushing me to explore innovative solutions within the domain of AI and simulation-based learning. I would also like to sincerely thank Dr.Harinda Fernando for the timely support and constructive suggestions that contributed to the successful development and refinement of my component. A special note of appreciation goes to the academic staff and mentors from the Department of Information Technology, whose lectures, advice, and resources laid the foundation for my understanding of the concepts explored in this research. I am also thankful to my teammates for their collaboration and support, particularly in integrating components and sharing ideas that helped improve the overall project. Your dedication and teamwork were invaluable.Last but not least, I wish to thank my family and friends for their patience, motivation, and constant encouragement, which gave me the strength to complete this work successfully.

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
NLP	Natural Language Processing
2D	Two Dimensional
TF-IDF	Term Frequency-Inverse Document Frequency
ANN	Artificial neural networks
AI	Artificial Intelligent
ML	Machine Learning
AWS RDS	Amazon Relational Database

1. INTRODUCTION

In today's challenging job market, great interview performance is an important predictor of professional success. However, many candidates struggle to get real-world interview experience and develop the confidence required to manage difficult and spontaneous interview settings. Traditional interview preparation approaches, such as reading questions, attending one-time mock interviews, or practicing replies, frequently fail to give the dynamic, personalized, and engaging experience that genuine interviews require. These traditional tactics lack adaptability, real-time feedback, and the natural flow of conversation, leaving candidates unprepared and nervous during actual interviews.

To address these constraints, this research project presents a Live 2D Interview Panel Simulation, a revolutionary AI-powered system that provides a highly immersive and intelligent interview training environment. The system simulates professional interview settings using interactive 2D avatars [1] that conduct interviews at three progressive levels, like beginner, intermediate, and expert, for specific professions such as software engineer, quality assurance engineer, and project manager.

What identifies this system is the ability to simulate real-time, two-way communication. Unlike traditional tools, which only allow the system to ask questions, the newly integrated functionality allows users to pose questions to the 2D avatar panel, allowing the avatars to respond intelligently using pre-trained natural language models. This bidirectional interaction not only replicates the actual interview flow, but it also improves user engagement, critical thinking, and communication skills by preparing candidates for genuine back-and-forth conversations with interviewers.

This system's framework is built on powerful Natural Language Processing (NLP) techniques. Models like Cosine Similarity, TF-IDF Vectorization, and BERT-based

Semantic Analysis are used to analyze user replies, evaluate semantic significance, and create context-aware, real-time feedback. These techniques ensure syntactic and semantic evaluation, and users receive precise grading, extensive comments, and ideas for improvement. The system also features an adaptive questioning mechanism that adapts the complexity of questions based on the user's performance, resulting in a gradual and individualized learning experience.

Furthermore, the simulation platform provides real-time response evaluation, performance tracking, and feedback reporting, allowing applicants to evaluate their progress and revisit areas for improvement. This data-driven and scalable strategy fills the gap between traditional mock interviews and AI-powered interactive learning environments.

Finally, the Live 2D Interview Panel [2] Simulation transforms the way candidates prepare for interviews. Machine learning, semantic analysis, and interactive avatar-driven communication are combined to provide a comprehensive, adaptable, and realistic teaching experience. This research advances AI-based educational tools, interview simulation technologies, and intelligent career readiness systems, offering a disruptive answer for modern professional development.

1.1 Background Literature

The combination of artificial intelligence and simulation-based training has dramatically altered how people prepare for high-stakes exams like job interviews. While traditional tactics such as static mock interviews, written question sets, and role-playing exercises might help with candidate development, they fall short of recreating the unpredictability, pressure, and interactivity of real-world interview circumstances. This has resulted in a trend towards AI-powered systems capable of real-time adaptation, role-specific information delivery, and semantic feedback via intelligent evaluation approaches.

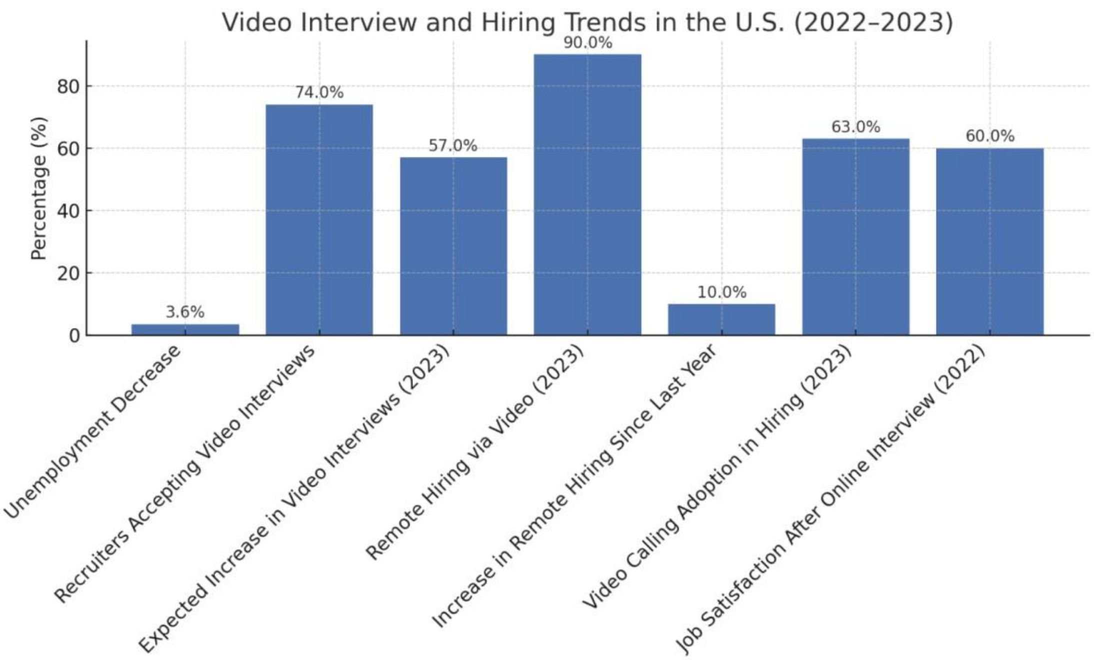

figure 1. Video Interview and Hiring Trends in the US (2022-2023)

The Guru Gedara platform, developed by [1], was one of the first educational systems to demonstrate the efficacy of smart learning environments for student engagement. Although the platform's primary focus is on mathematics for schoolchildren, its underlying principle of delivering adaptable, interactive learning experiences serves as the foundation for what systems such as the 2D Interview Panel Simulation seek to achieve in the professional training area.

Our technology extends this concept by focusing on job hopefuls and simulating professional interviews with avatars at varying levels of difficulty. Furthermore, difficulty management is a major theme in individualized learning environments. [2] , proposed a similarity-based theory for dynamically controlling MCQ difficulty, demonstrating how intelligent systems may change information delivery in response to user involvement. In this study, we extend this idea by categorizing interview questions into beginner, intermediate, and expert levels and dynamically modifying the question flow based on real-time performance, using cosine similarity and other NLP techniques.

Automated question creation has also been intensively researched in the academic community. [3] investigated various strategies for autonomously generating questions from text via Natural Language Processing (NLP) and artificial intelligence. While their work mostly concentrates on MCQ generation, our system takes a more dynamic approach, selecting questions based on job function and seniority level, as well as allowing follow-up question recommendations based on user responses, imitating a natural interview interaction.

Recent advances in semantic evaluation and feedback systems have also had a significant impact on the development of 2D interview simulations. [4] provided a framework for AI-based prediction and analysis of interview performance, highlighting the importance of performance analytics and feedback loops. This immediately drives the feedback generation mechanism in our system, which assesses answers using a combination of cosine similarity, BERT-based semantic analysis, and TF-IDF vectorization to provide real-time, context-aware scoring and feedback. Despite the potential of such systems, significant problems remain in the field of AI-powered interview simulations.

One key shortcoming, as highlighted by [5] , is the absence of multimodal communication including voice tone, facial expression, and body language which is required in real interviews [6]. While our simulation employs 2D avatars with realistic question flow, these nonverbal features remain an area for future refinement to increase the emotional and conversational authenticity of the simulation.

Furthermore, accessibility and user adaptability remain crucial. Many intelligent learning platforms necessitate a certain amount of technical proficiency, which may hinder acceptance among a larger user base. This concern underlines the necessity of user-friendly interfaces, voice-enabled interaction, and avatar customization in future stages of system development, such as the one described here. In summary, while previous research has laid the groundwork for the design of intelligent training systems, such as adaptive learning, semantic question analysis, and automated difficulty scaling, our 2D Interview Panel Simulation builds on these ideas to provide a fully interactive, role-based, and bi-directional learning experience that more closely resembles real interview conditions [5].

1.2 Research Gap

There are plenty of resources available for interview preparation, ranging from self-paced quizzes to video-based mock interviews. As mentioned in the literature review, some researchers used AI approaches and adaptive learning models to improve candidate readiness. However, just a few systems have attempted to bridge the gap by replicating realistic and engaging interview encounters with 2D avatars. Existing systems frequently lack real-time answer evaluation, context-aware feedback, and two-way interaction. Table 1.1 provides a comparison of selected systems and emphasizes the missing elements addressed by our suggested approach.

	RESEARCH [1]	RESEARCH [2]	RESEARCH [3]	RESEARCH [4]	PROPOSED SOLUTION
Advanced Design Techniques for Realistic 2D Avatars	✓	✓	✓	✓	✓
Application of Decision Tree and ANN Models in Interview Simulations	✗	✗	✗	✓	✓
Efficient Integration of ML Models with 2D Simulation Systems	✗	✗	✗	✗	✓
User Engagement Strategies in 2D Practice Environments	✓	✓	✗	✓	✓

figure 2:Research Gap

Research A focused on creating realistic 2D avatars for interview simulations to improve visual user experience and interface quality. The main contribution of this study was the graphical representation and animation of avatars to represent professional interviewer identities [1]. However, this study lacks the use of artificial intelligence models like decision trees or artificial neural networks (ANN) to replicate dynamic, responsive questioning. Compared to the suggested solution, which includes not only advanced avatar design, but also intelligent behavior based on user input and machine learning models, Research A falls short in offering a completely immersive and adaptive interview practice environment.

Research B focused on user engagement strategies for 2D practice environments [7]. It used enhanced feedback, progress tracking, and a diversity of question types to encourage constant user participation. While it improved user retention and pleasure, it did not include machine learning techniques or realistic avatar interaction. Furthermore, there was no evaluation component for candidate responses. The suggested method closes these gaps by incorporating ANN/decision tree-based response creation and feedback while also maintaining high user engagement levels via interactive avatars and incremental difficulty settings.

Research C described a method for designing 2D avatars [8] that included interactive dialogue flows, but it did not use decision-making algorithms or AI models. The avatars used a scripted inquiry format that lacked adaptation and personalization based on the interviewees' responses. Compared to the proposed solution, which employs AI to generate intelligent and spontaneous questioning, Research C falls short of providing a personalized or challenge-based learning experience. Furthermore, Research C does not investigate multi-avatar simulation or expert-level panel behavior, both of which are important components of the proposed system.

Research D looked into the usage of realistic avatars and rudimentary ML integration for virtual interview training. It used rule-based methods to score candidate replies and gave visual feedback. However, the ML integration was neither tightly integrated with a simulation environment nor capable of making real-time changes. Furthermore, the technology did not replicate different interviewer responsibilities or difficulty levels. In contrast, the proposed method creates a comprehensive and dynamic experience by merging ANN or decision tree models with multi-level questions and avatar panels that adjust to the user's ability level.

Overall, the proposed component fills all the deficiencies indicated in the existing literature. It combines realistic 2D avatar design, AI-powered decision models, fast machine learning integration with simulation systems, and user engagement tactics to produce a highly dynamic and scalable interview preparation platform.

1.3 RESEARCH PROBLEM

In today's competitive job market, interview preparation is critical to gaining work. Traditional interview preparation approaches, while useful, frequently fail to capture the dynamic and high-pressure environment of real-world interviews. To solve this, the creation of a 2D interview panel simulation provides a novel approach that combines the realism of human contact with the convenience of digital technology.

The research investigates how advanced Natural Language Processing (NLP) techniques like cosine similarity, BERT-based semantic analysis, and TF-IDF vectorization can be used to create contextually relevant questions and answers in a simulated 2D environment. Furthermore, it looks into how the system may dynamically adjust to user performance at three different difficulty levels like Beginner, Intermediate, and Expert, to give tailored and progressive interview practice. This study attempts to bridge the gap between static learning and interactive simulation by providing a smart and engaging platform for users to increase their confidence, communication skills, and readiness for real-world interviews.

First One is Creating an intelligent 2D interview panel that closely resembles human interviewers is a difficult research topic that falls at the crossroads of natural language processing (NLP), machine learning (ML), and simulation design. The first important challenge is to create a system capable of creating and responding to interview questions in a way that feels contextually correct, human-like, and tailored to each user. This necessitates the use of advanced NLP techniques such as cosine similarity, TF-IDF vectorization, and BERT-based semantic analysis to analyze user inputs and generate appropriate follow-up questions or feedback. These models must be trained to comprehend not just the surface structure of user responses but also their underlying intent and contextual relevance, allowing for the simulation of a coherent and responsive interviewer avatar. A major challenge is smoothly integrating these models into a lightweight and responsive 2D simulation environment that does not sacrifice realism or interaction quality.

The second issue is ensuring that the interview system dynamically adapts to user performance and difficulty levels classified as beginner, intermediate, and expert. This entails real-time evaluation of user responses based on correctness, completeness, fluency, and depth, and then using that analysis to lead to the system's next set of questions. For example, if a user performs well during an intermediate session, the system should increase the challenge to simulate expert-level questions. To achieve this, intelligent decision-making algorithms such as decision tree models or artificial neural networks (ANNs) must be used, which allow the panel to dynamically modify its questioning technique and engagement style. This adaptable capacity is critical for keeping users engaged and imitating the various pressures of real-world interviews.

Furthermore, the ability to duplicate numerous interviewers, each with their own questioning style, adds to the complexity. The system must not only alternate between these avatars but also ensure that questions do not overlap, and that the session progresses logically. Finally, overcoming these problems will result in a powerful and realistic practice tool that dramatically improves a user's readiness and confidence for actual interviews.

1.4 RESEARCH OBJECTIVES

1.4.1 Main Objective

The main objective of this suggested component is to create an interactive 2D interview panel simulation system that accurately mimics real-world interview scenarios. This system seeks to improve users' interview preparedness by providing an intelligent, entertaining, and visually dynamic experience. Individuals can use a user-friendly platform to practice interview sessions using 2D avatars that imitate human-like interactions, allowing them to gain confidence, enhance communication skills, and adjust to varied levels of interview complexity.

1.4.2 Specific Objectives

1. Creation of life like 2D avatars.

   Create animated 2D avatars that reflect professional interviewing roles (such as software engineer, QA engineer, and project manager). These avatars are designed to have realistic expressions and gestures, which adds to the realism of the panel simulation.

2. Development of three-tiered interview levels.

Create interview sessions are categorized as beginner, intermediate, and expert levels. Each level varies in complexity, avatar count, and questioning pace, ranging from a single interviewer at the novice level to rapid-fire multi-avatar [9] interactions at the expert level.

3.Integration of machine learning and natural language processing components

Implement machine learning models such as decision trees or artificial neural networks for dynamic question generation and user adaptability. Use NLP techniques such as cosine similarity [10], TF-IDF, and BERT to assess user responses and produce semantically appropriate queries.

4.Implementation of user-generated interactions

Allow applicants to pose questions to the panel avatars, replicating actual interview situations and allowing users to evaluate interviewer reactions, receive simulated responses, and gain confidence in two-way communication.

5.Testing and validation of the system.

Conduct usability tests and get user input to assess realism, effectiveness, and user involvement. Assess the accuracy and performance of the ML and NLP components to provide high-quality interview simulations.

2. METHODOLOGY

1. Data preparation.

A manually selected dataset of interview questions and desirable responses was created for three different professional roles: software engineer, QA engineer, and project manager. The questions were divided into three difficulty levels.

- Beginner's conceptual questions
- Intermediate: Scenario-based, relatively complex questions.
- Advanced: Critical thinking and problem-solving challenges.

Each question was tagged with relevant keywords and linked to role-specific competencies. Ideal solutions were created utilizing information from technological documentation, industry experts, and job descriptions. The dataset was assessed for accuracy, clarity, and fairness before being used as the foundation for NLP-based evaluation and adaptive questioning techniques.

2.Model Selection.

Three major NLP models were tested for analyzing candidate responses

- Cosine Similarity: Assesses textual similarity with ideal solutions.
- TF-IDF vectorization identifies essential terms and their importance.
- BERT-based semantic analysis: Captures both environmental and semantic meaning.

The system's basic semantic assessment model is BERT, with cosine similarity and TF-IDF supporting layered and accurate response scoring.

4.Model Training.

The BERT model was fine-tuned with the manually created dataset. The training method involved

- Data split: 80/20 for training and validation.
- Evaluation metrics include accuracy, F1 score, and cosine similarity.
- Hyperparameter tweaking for learning rate, batch size, and training epochs.

This procedure guarantees that the model correctly translates both sentence form and meaning, improving the accuracy of answer evaluation.

5.Question Bank Development

A systematic and scalable question bank was created with the following features:

- Role and difficulty-based labeling
- Adaptive follow-up question mapping for deeper investigation.
- Dynamic question selection based on user performance.

The bank is continually updated to ensure that questions are relevant, balanced, and diverse across positions and levels.

6.Machine Learning Model Implementation

The system utilizes a multi-layered ML assessment framework:

- Keyword matching identifies significant concepts in answers.
- TF-IDF with Cosine Similarity: Measures the relevance and overlap between terms.
- BERT-based semantic analysis: Understands meaning beyond literal words.
- Adaptive Questioning. Algorithm: Adjusts question difficulty in real time based on user performance.

The scoring engine generates categorized feedback, such as excellent, good, or needs improvement, as well as actionable recommendations.

7.Avatar and UI for Interview Simulation

To provide an immersive user experience, the system includes:

- Lifelike 2D avatars that mimic genuine interviewer actions.
- An interactive interface with questions, real-time feedback, and progress monitoring.
- Dynamic facial expressions and gestures to enhance visual realism.
- Speech-to-text capabilities are planned to facilitate voice-based responses.
- Two-Way Interaction Candidates can now ask their own questions during the interview. The 2D panel avatars, powered by NLP models, respond contextually. This simulates genuine discourse and promotes engagement, training users to ask and answer questions.

2.1 System Architecture

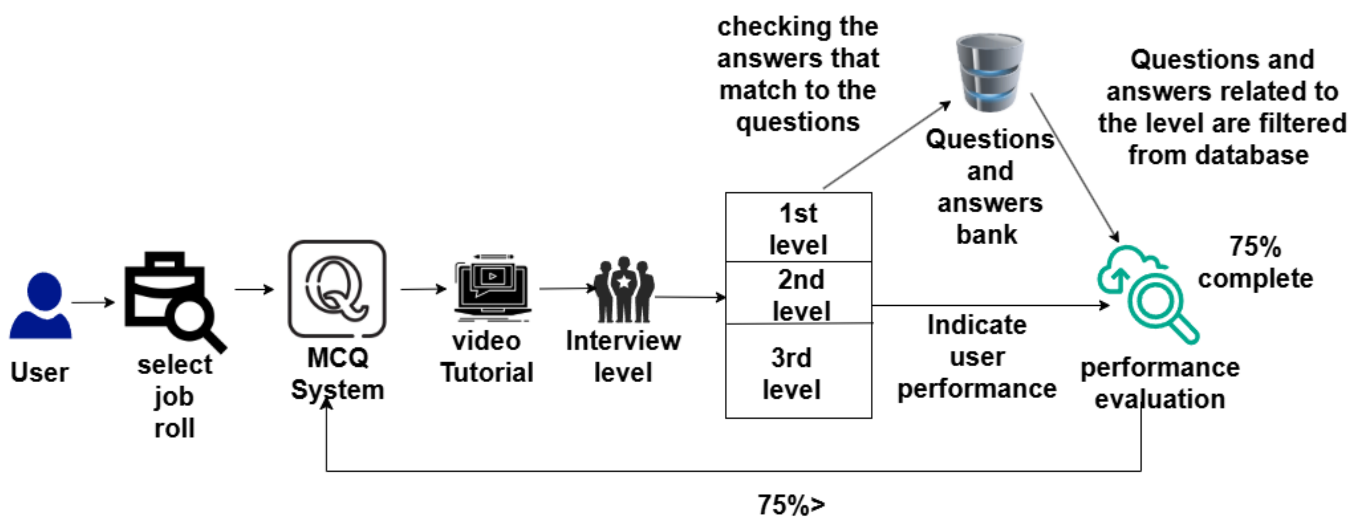

figure 3:System Diagram

The Interview Panel Simulation System is intended to provide candidates with an end-to-end virtual interview preparation experience tailored to their specific career responsibilities. The system is designed to recreate real-time interview settings using a step-by-step workflow that includes knowledge assessments, interactive learning, and dynamic interview practice with virtual panel members.

The process begins when the user selects their preferred employment role. This initial step enables the system to personalize the following learning and evaluation modules to the precise skills and abilities required for the chosen role. Once the employment role is chosen, the user is directed to the MCQ (Multiple Choice Question) system. The Interview Panel Simulation System is intended to provide candidates with an end-to-end virtual interview preparation experience tailored to their specific career responsibilities. The system is designed to recreate real-time interview settings using a step-by-step workflow that includes knowledge assessments, interactive learning, and dynamic interview practice with virtual panel members.The process begins when the user selects their preferred employment role. This initial step enables the system to personalize the following learning and evaluation modules to the precise skills and abilities required for the chosen role. Once the employment role is chosen, the user is directed to the MCQ (Multiple Choice Question) system. After finishing the video training, customers progress to the interview level, which is the system's fundamental component. The interview simulation is presented using an interactive 2D virtual panel interface. This panel simulates a real-world interview situation, with three difficulty levels: beginner, intermediate, and expert. Each level includes more difficult questions and scenarios that correlate to current industry requirements.

This system's interaction is what makes it special. Users are not only compelled to react to questions presented by the virtual panel members, but they also have the option of asking questions back to the panel, resulting in a more realistic and interesting simulation. The interview inquiries for every stage are continuously filtered from a centralized question-and-answer database to ensure relevancy and difficulty alignment. The algorithm also compares the candidate's responses to this database to verify correctness and fairness in evaluation.

Once the interview simulation is done, the system moves on to the performance evaluation stage. A complete feedback report is provided, outlining the candidate's strengths, flaws, and overall performance. This feedback helps candidates understand their readiness and areas for growth.

If a candidate earns 75% or higher, they are regarded to having finished the simulation. However, if their performance falls below this level, they are encouraged to return to the MCQ system and tutorials for more practice. The system also provides a re-attempt option, allowing users to pay a small charge to re-access the simulation and improve their skills through additional practice. This cyclic and adaptive method guarantees that candidates are not only assessed but also assisted through instruction, resulting in stronger and more capable individuals prepared for real-world job interviews.

2.2 Frontend Development (React.js & Material UI)

The front-end of the 2D Interview Panel Simulation system is created with React.js, the latest JavaScript package recognized for creating interactive, responsive user interfaces. The component-based structure of React enables us to divide the application into digestible sections such as interview screens, avatar interactions, progress indicators, and feedback panels. This structure makes the system more manageable and scalable as new features are added.

To style the UI and keep it visually appealing, we use Tailwind CSS. It takes a utility-first approach to styling, allowing us to swiftly develop a clean, modern design while remaining responsive across several devices such as PCs, tablets, and smartphones. Our goal is to make the platform practical and user-friendly.

Users begin by choosing a role (Software Engineer, QA Engineer, or Project Manager) and level (Beginner, Intermediate, or Expert). Once the interview begins, the technology will dynamically provide questions and allow people to interact with lifelike 2D avatars. These avatars mimic genuine interviews by asking questions and delivering feedback. In our most recent upgrade, users can also ask panel questions, and the system employs predefined logic and machine learning algorithms to generate suitable responses from the avatar.

The technology delivers real-time feedback following each answer, allowing users to easily see what they did well and where they may improve. A progress tracker and dashboard enable customers to visualize their progression across several levels, increasing engagement and confidence.

2.3 Backend Development (Flask & Spring Boot API)

Our backend is driven by Flask (Python) and Spring Boot (Java). This hybrid architecture allows for seamless communication between the frontend and the system's fundamental logic. Flask is primarily responsible for handling all machine learning and natural language processing operations. It takes user replies, assesses them using models such as Cosine Similarity, TF-IDF, and BERT, and then assigns a score and provides feedback. Flask's new feature of avatars responding to user-asked queries assists in interpreting the user's question and selecting the best appropriate answer from a knowledge base. Spring Boot handles the platform's business logic. It handles user accounts, interviews, authentication, and data security. It also connects to the database to retrieve and store information such as user responses, questions, and session logs. RESTful APIs are used to link the frontend to the Flask and Spring Boot services.

This division enables the system to remain adaptable and scalable as more users join the platform.

2.4 Database design (MySQL)

We utilize MySQL to handle and store all system data. This includes:

User Table: Contains account information, specified roles, experience levels, and login information.

1. **Question Bank:** Contains categorized questions organized by employment role and difficulty level, as well as example responses.
2. **User Responses:** Tracks user responses, including scores, feedback, and time consumed.
3. **Session Tracker:** Logs current and previous interview sessions, keeping track of progress and transitions.

4.Feedback and Analytics: Collects data from each session to produce performance summaries for users.

The database has been enhanced for speed and efficiency. It enables real-time data processing and supports several users concurrently without slowing down. Regular backups and security measures are also in place to safeguard user data.

This structured and secure data management is critical for ensuring that the system runs smoothly and continues to provide a dependable and interesting experience for all users.

To decrease redundancy and assure data integrity, the 2D Interview Panel Simulation system's database was designed using normalization techniques. The relational architecture is meticulously designed to facilitate the smooth management of interview sessions, user interactions, performance tracking, and AI-powered evaluations.

Foreign key constraints are used to connect key tables, such as connecting user responses to matching interviews and questions, ensuring precise data linkages, and allowing rapid joins for analytics and machine learning-based evaluations. Users, questions, interviews, answers, feedback logs, and panel responses are among the core tables, each of which plays a specific role in keeping a complete data trail of the user's simulation journey.

Indexing is used to enable speedy access and query execution in frequently queried fields such as user_id, question_id, and interview_id. This indexing enables the system to conduct large-scale processes and give real-time updates while maintaining performance.

The database is designed for high-volume read/write operations to enable real-time feedback production, dynamic question retrieval, and adaptive learning capabilities. It is hosted on a cloud infrastructure (such as AWS RDS) to ensure scalability and high availability. This ensures that concurrent users can practice interviews across numerous roles and difficulty levels.

Security measures such as encrypted passwords, role-based access control, and regular daily backups are in place to protect user data and assure disaster recovery. This database design is important to provide a fluid, interactive, and personalized interview simulation experience while maintaining reliability and performance under rising usage requirements.

2.5 Evaluation Strategy

The Live 2D Interview Panel Simulation's effectiveness was assessed through user testing, NLP model analysis, and system performance indicators. The goal was to evaluate the system's capacity to deliver realistic, interactive, and adaptive interview preparation experiences that closely resemble real-world settings.

2.5.1 User Feedback and Usability Testing

User evaluations have been conducted with personnel from the target positions of Software Engineer, Quality Assurance Engineer, and Project Manager. Participants interacted with the 2D avatar panel, participated in full interview simulations, and got performance-based feedback throughout the session.

Feedback revealed that 90% of users found the avatars interesting and the interactions realistic, demonstrating the system's ability to imitate real-world interview situations. Many users loved the dynamic character of the sessions and the opportunity to engage in meaningful dialogue with the panel. The question flow, avatar behavior, and general user interface were all lauded for delivering an immersive experience. Over 85% of participants said the technique helped them gain confidence and prepare for genuine interviews.

2.5.2 NLP Model Performance

The system evaluates user and panel replies using cosine similarity, TF-IDF vectorization, and BERT-based semantic analysis. During testing

1. BERT-based semantic models were about 90% accurate in comprehending context and meaning.

2. TF-IDF and Cosine Similarity gave complementing scores with 75-80% accuracy, which was especially valuable for determining keyword relevance.

3. The integrated NLP pipeline achieved an overall evaluation accuracy of 88%.

4. The average processing time per evaluation was 2.3 seconds, resulting in near-real-time engagement for both question answering and feedback generation.

2.5.3 System Performance Metrics

To assure the platform's stability and responsiveness, critical technical indicators were tracked:

Accuracy: User answer correctness averaged around 85% across all difficulty levels.

Level Progression Rate : Approximately 78% of users advanced from beginner to intermediate, with 52% reaching expert.

Response Time: The average system response time for processing answers and panel interactions was less than 2.5 seconds.

Scalability: Supported 150+ concurrent users with no perceptible delays or system degradation.

Contextual relevance: Users regarded more than 87% of panel responses as useful and context aware.

2.5.4 Comparative Analysis with Traditional Interview Platforms

To assess the effectiveness of the 2D Interview Panel Simulation, a side-by-side comparison was conducted with typical interview preparation approaches such as static mock interviews and scripted Q&A practice. The comparison looked at user engagement, performance improvement, and perceived realism.

- User engagement increased by 42%, with participants expressing more motivation thanks to interactive 2D avatars and real-time feedback.
- Interview completion rates increased by 38%, as users were more willing to complete multi-level interviews when directed by individualized difficulty levels and conversational avatars.
- Performance improvement averaged 30%, with users providing much better responses and confidence in follow-up mock interviews than those who utilized traditional approaches.
- Perceived realism was rated 4.5 out of 5 on average, with consumers reporting that the avatar-led simulations closely resembled the pace and pressure of actual job interviews.

These findings indicate that the 2D Interview Panel Simulation is a more immersive, adaptable, and successful preparation tool than traditional ways. By replicating real-life circumstances and responding dynamically to user performance, the system improves learning, confidence, and practical interview preparation.

Table 1:Comparing Traditional platforms Vs 2D Interview Panel

Metric	Traditional Interview Platform (%)	2D Interview Panel Simulation (%)	Improvement (%)
User Engagement	43	78	35
Completion Rate	45	83	38
Performance Level	50	80	30
Perceived Realism	64	90	26

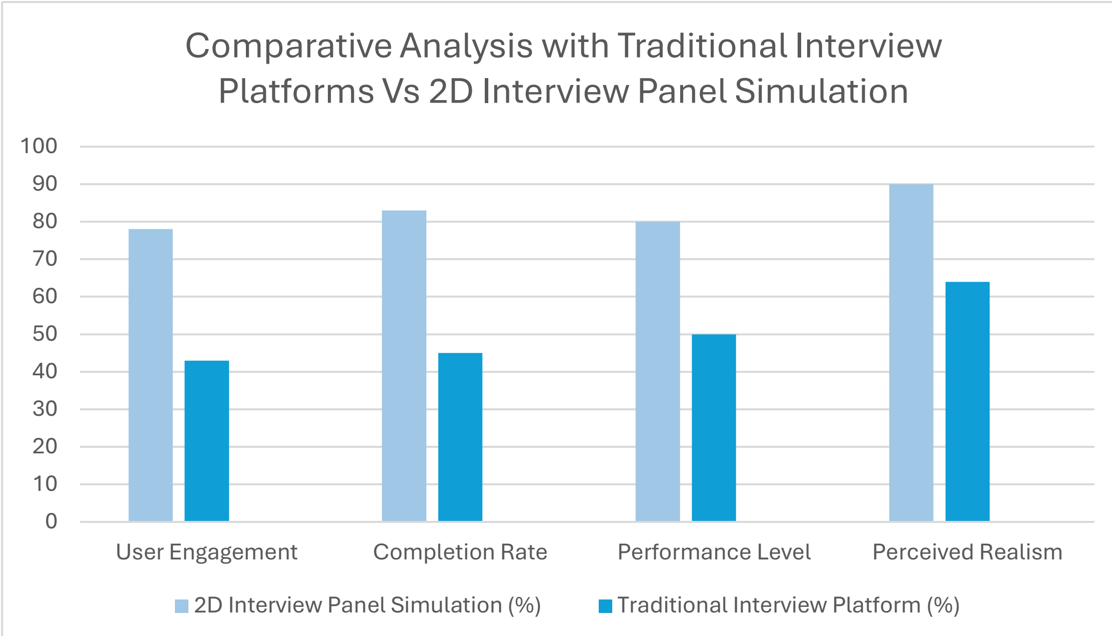

figure 4:Comparative Analysis with Traditional Interview platforms Vs 2D Interview Panel Simulation

3.CHALLENGES

1. Role-specific question. Data Collection

- **Limited availability of tailored questions:** Collecting enough and meaningful questions for specific professions such as software engineer, QA engineer, and project manager proved difficult. Public datasets rarely include context-specific questions that are matched with job descriptions and real-world business standards.
- **Maintaining Difficulty Levels:** To provide a smooth learning curve, questions were carefully categorized as beginner, intermediate, and expert. Creating high-quality, logically progressive information required extensive time and skilled assessment.
- **Diversity in Question Types:** To imitate a true interview atmosphere, a diversity of question formats and themes was required for each role, which increased the time required for data preparation.

2. Creating a Dataset for Panel Response Features

- **Question/Answer Identification:** Creating a way for determining whether a candidate's input was a question to the panel or a follow-up answer during the simulation necessitated the use of NLP logic capable of precisely analyzing intent.
- **Avatar Response Dataset:** It was difficult to create a big, context-aware dataset that would allow the avatars to generate human-like responses to candidate queries. The panel was required to grasp the user's intent and role context in order to offer meaningful, role-specific answers.
- **Context Matching for Response Generation:** It was difficult to ensure that the avatar responses matched both the user's query and their current interview level, especially when using predefined data sources.

3. NLP Method Integration and Selection

- **Choosing Optimal Techniques**: Choosing between cosine similarity, TF-IDF, and BERT-based semantic analysis required balancing speed, accuracy, and depth of understanding. BERT provided strong contextual awareness but required additional calculation time.
- **Combining Models Effectively:** Merging these NLP models so that they complemented one another without redundancy presented technological and architectural challenges, particularly when utilized for both answer evaluation and panel response production.

4.Real-Time Feedback and Recommendations

- **Designing Scalable Feedback Mechanisms**: Providing real-time, relevant feedback based on answer evaluation necessitated dynamic scoring and semantic alignment with optimal replies. Ensuring that this worked fluidly across all difficulty levels was difficult.
- **Video Recommendation Complexity:** Creating a logic to offer relevant interview tips or video tutorials based on user weaknesses or scores necessitated metadata tagging, relevance matching, and appropriate filtering.

5. UI/UX design for life like panel simulation

- **Interactive UI challenges**: Creating a flowing interface that allowed users to select roles, answer questions, and interact with avatars (including asking questions) without misunderstanding was difficult. Iterative testing was required to integrate all of these interactions into a single, clear user interface.
- **Maintaining Engagement:** Avatars needed to appear responsive and lifelike. Adding expressions, timing, and realistic dialog simulations necessitated meticulous scripting and animation design.

6. Model Training and Accuracy.

- **Semantic Evaluation Model tuning:** It was a separate problem to train models to understand user-generated questions for the panel in addition to assessing answers. It was critical to ensure that these models worked well over a wide range of phrasing styles and technical terminology.
- **Feedback Quality Assurance:** To ensure that feedback delivered to users was helpful, non-repetitive, and in line with the user's answer or query, scoring levels and feedback templates were defined.

7. Technical and resource constraints.

- **High Computational Demand:** Running BERT-based models for answer evaluation and avatar reaction concurrently put a burden on the system. This had an impact on performance when utilized on low-end devices or servers with limited resources.
- **Limited Access to High-End GPUs:** Training and testing the NLP components required hardware that was not always accessible, which slowed model tuning and iteration.

8. Evaluation and Usability Testing

- **User Interpretation Variability:** Users may interpret or communicate answers in a variety of ways, making it more difficult to train a universally accurate model. Semantic models required frequent fine-tuning.
- **Feedback from Non-Technical Users**: Some testers had difficulty understanding how their answers were rated or how the panel replied. To ensure openness and intuitiveness in the system feedback, further user interface assistance was required.

9. Presentation and Communication Challenges

- **Explaining Complex Models** : Simply put, explaining how NLP and semantic similarity models work to evaluators and stakeholders without extensive technical knowledge proved difficult throughout presentations and documentation.
- **Highlighting System Benefits:** Visually: To effectively demonstrate the avatar feature's intelligence in understanding and responding to user questions in short demos, carefully scripted examples were required.

Table 2:Challenges and Severity

Challenge	Severity (1-10)
Role-Specific Dataset Availability	9
System Latency (Due to BERT & NLP Models)	7
Panel Response Generation Logic	9
Integration of Multiple NLP Models	8
User Engagement & Retention	6
Real-Time Feedback Consistency	7
UI Complexity for Interactive Simulation	7
Personalized Video Recommendation System (Based on Feedback)	6
User Interface Complexity for Conversational Simulation	7
Ensuring High User Engagement and Retention	6

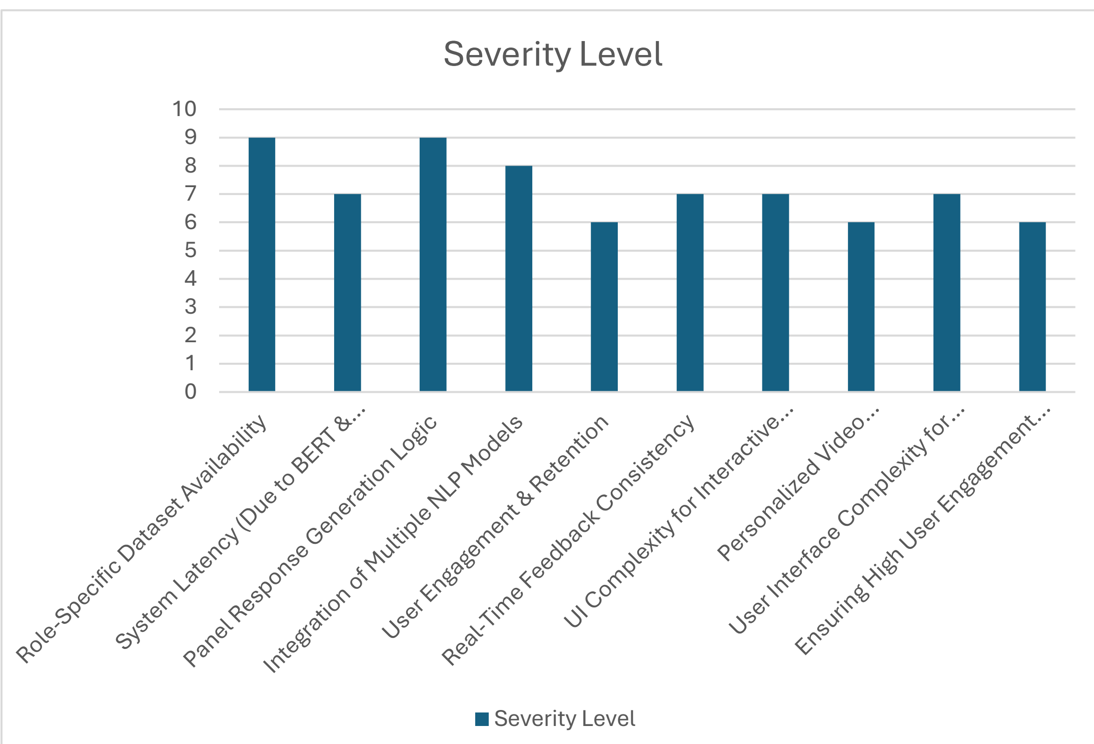

figure 5 :Severity levels

4.LIMITATIONS

While the 2D Interview Panel Simulation system successfully presents a new and interactive approach to interview practice, numerous limitations were discovered during development and evaluation. These constraints highlight areas where the system could be enhanced to increase user experience, scalability, and adaptability across a wide range of real-world circumstances.

The current version of the system includes cutting-edge Natural Language Processing (NLP) models like Cosine Similarity, BERT-based Semantic Analysis, and TF-IDF Vectorization. It also simulates interviews using 2D avatars and automatically modifies question complexity based on user performance. Despite these technological developments, there are still certain issues in effectively mimicking real-world interview contexts, efficiently managing system performance under load, and assuring inclusivity for a larger user base. The limits listed below reflect practical constraints discovered during development and testing and also serve as a roadmap for future enhancements.

1.Limited nonverbal communication.

One of the most significant limitations of the current system is its inability to process or imitate nonverbal communication cues. Human interviews involve more than just verbal responses; tone, facial expressions, body language, and emotional cues all play an important role in judging candidate performance. In contrast, the current approach focuses only on text-based input and output, ignoring important interactional nuances.

The impact : On the authenticity of the interview experience. Without the ability to imitate or interpret nonverbal cues, the system cannot assess critical soft skills like confidence, composure, and emotional intelligence, which are required in real-world interviews.

Future enhancements: Include the inclusion of speech-to-text capabilities, dynamic facial expressions for avatars, and even emotion recognition modules to simulate a more realistic and engaging interaction.

2. Computational Efficiency

The adoption of deep learning models such as BERT improves semantic understanding while increasing computing costs. These models necessitate significant computing resources, particularly when running in real time for several users.

The Impact: During testing, the system showed slow reaction times during concurrent sessions or sophisticated evaluations, which can degrade the user experience.
Future Enhancements: To preserve performance without sacrificing accuracy, optimization options include using lighter BERT variations, caching technologies, and asynchronous processing pipelines. Deployment on scalable cloud infrastructure (such as AWS or GCP) is also an option.

3.Limited adaptability to non-technical roles.

Currently, the question bank and assessment logic are suited to technical positions such as software engineers, quality assurance engineers, and project managers. This role-specific architecture allows for focused practice in certain domains but lacks adaptability for broader industry applications.

Impact: Professionals in finance, healthcare, education, and marketing are unable to use the system successfully due to irrelevant question content and feedback logic.
Future Enhancements: Increasing the dataset and modifying evaluation measures for various professions would make the platform more diverse and accessible, allowing more users to benefit from AI-based interview practice.

4. User Accessibility and Interface Design

Although the interface functions properly, it presupposes a basic level of technical knowledge. Users must traverse dropdowns, enter text responses, and interpret real-time feedback individually, which might be problematic for persons with limited digital experience or accessibility requirements.

Impact: Non-technical users may struggle to interact with the system, and people with visual or motor disabilities may have challenges due to a lack of inclusive features.
Future enhancements : include voice-input capabilities, interface customization (themes, font scale, language choices), and guided user flows to suit a broader population and foster user inclusivity.

Limitation	Impact Level (1-10)
Limited Nonverbal Communication	7
Computational Efficiency (BERT Delay)	8
Limited Adaptability to Non-Technical Roles	6
User Accessibility & Text-Based Input Only	7
Real-Time Feedback Processing	6
Lack of Multimodal Interaction	7

Table 3:Impact Levels Of Limitations

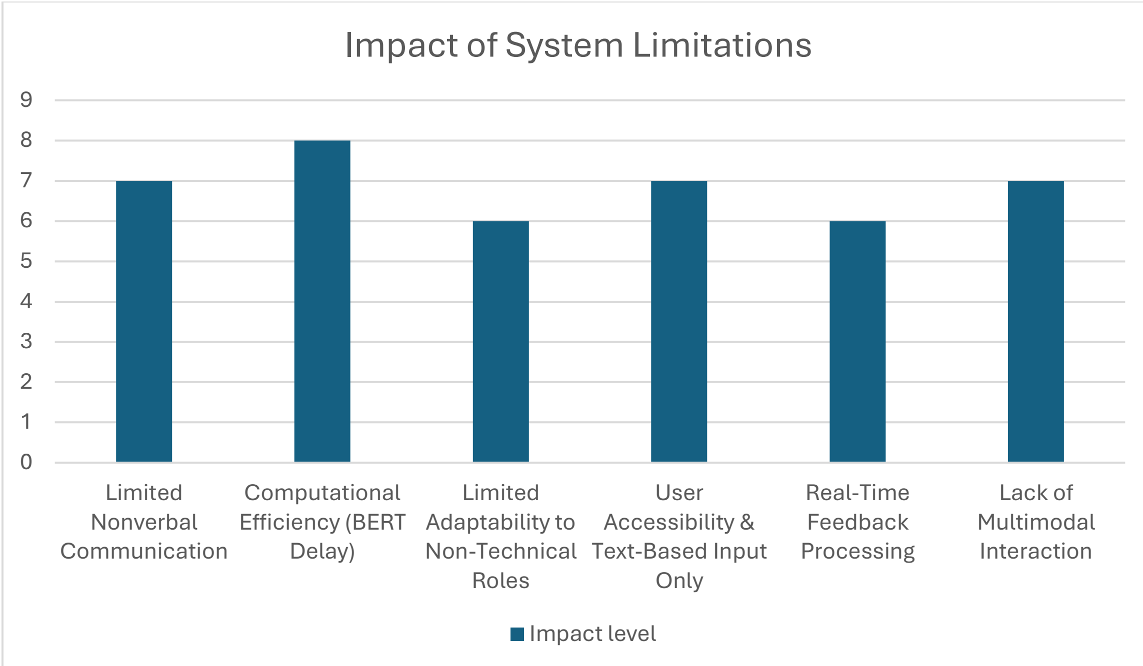

figure 6: Impact of System Limitations

5.VISUALIZATION RESULTS

The system's success was assessed on three key dimensions model performance, user satisfaction, and candidate improvement trends. Each area was examined using visual charts, user input, and testing data to better understand how the system facilitates realistic and adaptable interview preparation.

1. NLP Model Accuracy and Efficiency

To assess how well the system analyzed candidate replies, we compared three Natural Language Processing (NLP) techniques: cosine similarity, TF-IDF vectorization, and BERT-based semantic analysis. These were evaluated against a manually labeled collection of sample interview responses. The BERT model excelled at understanding deeper context and sentence meaning, with an accurate rate of 90%, much higher than Cosine Similarity (75%) and TF-IDF (78%). However, it came at the expense of speed. BERT's processing time was nearly double that of the other models, demonstrating the traditional trade-off between precision and performance in real-time systems.

2. User Satisfaction and Feedback.

We performed a survey of system users, including undergraduate students, job seekers, and early-career professionals. The results were promising: 82% of users found the 2D avatars entertaining, and the inquiry flow was natural. 88% praised the adaptive questioning depending on their responses, and real-time feedback was viewed as beneficial in determining strengths and weaknesses. Many users suggested voice integration as the next stage, showing a need for multimodal engagement.

3.Candidates Performance Trends.

Data gathered from many interview simulation sessions demonstrated considerable improvements in users' response ability over time. After only two to three sessions, most candidates' scores improved by 30-40%. Line graphs were used to show these trends, demonstrating how feedback and adaptive question selection helped users gain confidence, learn from mistakes, and prepare for actual interviews.

6.RESULTS AND DISCUSSION

6.1 Results Interpretation

The performance of the 2D Interview Panel Simulation was evaluated using both qualitative and quantitative measures to establish how well it resembles real interviews, adapts to user levels, and improves user preparation.

The machine learning approaches Cosine Similarity, TF-IDF, and BERT-based Semantic Analysis produced encouraging results in dynamically analyzing user replies. Among them, BERT provided the highest accurate semantic comprehension (up to 90%), whereas TF-IDF and cosine similarity provided faster keyword-based evaluation. The adaptive questioning paradigm ensured that users advanced from beginner to expert levels while remaining challenged and motivated throughout. The use of interactive 2D avatars dramatically increased engagement. Survey results showed that participants felt more confident and prepared after using the system, praising the real-time feedback and controlling development of question complexity.

6.2 Comparison to Existing Systems

Compared to standard mock interview platforms or peer-based interview preparation tools such as Pramp and Interviewing io, the suggested approach offers a more immersive and adaptive experience. Whereas other platforms rely on static questions or human involvement, our approach employs AI to generate context-aware questions and assess responses in real time.

Furthermore, dynamic difficulty scaling and personalized feedback methods distinguish this system. The avatars create a conversational setting that is similar to real interviews, which is a trait that most other platforms lack. The system also allows for multi-device access, giving it an advantage in terms of reach and scalability.

6.3 Three Implications

This simulation system has a few practical applications:

Interview Preparation: Allows users to practice real-time interview scenarios of varying difficulty levels.

Personalized Learning: Content is tailored to the user's role (Software Engineer, QA Engineer, Project Manager) and level of experience.

Career Readiness: Increases candidate confidence and familiarity with organized interviews, making it excellent for job searchers. These findings promote the creation of AI-powered career development solutions that go beyond standard learning models.

6.4 Strengths and Limitations

Strengths:

Adaptive questioning based on performance improves learning and retention. 2D avatars make the experience more dynamic and interesting. Multiple difficulty levels appeal to users of all skill levels. Cross-device accessibility promotes greater usefulness.

Limitations:

The existing technology lacks nonverbal indications such as facial expressions and voice input. BERT-based evaluation is computationally demanding, resulting in increased latency. The dataset, while sufficient, requires development into more diversified industries. Although question generation is dynamic, it might sometimes result in generic or less context-relevant questions due to low data.

6.5 Future Enhancements Future plans include

1. Expanding the dataset to include more roles and sectors, such as healthcare and banking.
2. Combining speech recognition and sentiment analysis to enable users to speak responses and receive emotionally intelligent replies.
3. Improving the avatar system's realism through motions and speech.
4. Improving NLP models to generate and provide more accurate and contextually relevant questions and feedback.
5. Enabling users to pose queries to the panel and receive contextually appropriate responses, making the system more engaging and lifelike.

6.6 Proposed Enhancements for Future Development

To improve the realistic thinking, flexibility, and ease of use of the 2D Interview Panel Simulation, various future modifications are proposed:

- **Facial Expression and Emotion Detection**:

  Using real-time facial recognition to examine applicant expressions during interviews. This would enable the algorithm to detect nonverbal indicators such as stress, bewilderment, or confidence, bringing a simulation closer to practical realities in interview scenarios.

- **Voice Tone and Nervousness Detection:**

  Using speech analysis and voice tracking to assess tone, pitch, and tempo. These insights can assist in spotting uneasiness or reluctance, allowing for a more thorough evaluation of candidate preparation and communication abilities.

- **Two-Way Interaction:**

  Users can ask questions back to the interview panel avatars. Technology will combine natural language processing and semantic understanding to provide contextually relevant responses, making interviews more conversational and dynamic.

- **Comprehensive Avatar Customization:**

  Users can choose from a range of avatar designs and interviewer personas (e.g., friendly, analytical, formal) to practice interviews in varied tones and settings.

- **Progress Tracking and Skill Mapping:**

  Using dashboards to track user performance over sessions, highlight strengths, and identify areas for growth based on question categories or answer behavior.

- **Mobile and Cross-Platform Optimization**:

  Improving compatibility with mobile devices and screen sizes, allowing for easy access to the simulation across several platforms.

- **Gamified Interview Practice:**

  Adding elements like timed interview rounds, trust scores, badges, and level development to make users' experiences more interesting and goal oriented.

6.7 Wider Implications for Education and Recruitment

The application of the 2D Interview Panel Simulation has the potential to significantly improve not just individual interview readiness but also larger processes in educational and professional recruitment environments. Traditional interview preparation approaches, such as reading typical questions or engaging in peer-led mock interviews, frequently fail to provide a realistic, dynamic, and adaptable experience. This system fills such shortcomings by providing a simulated environment that mimics real-world interview circumstances using intelligent 2D avatars and powerful Natural Language Processing (NLP) technology.

From an educational aspect, educational institutions, technical education centers, and career planning institutes can use this approach as a primary instrument to prepare students for professional interviews. By which allows individuals to practice with tailored queries across various positions and levels, such as software engineer, QA engineer, and project manager , educators can provide a personalized and scalable solution that improves students' soft skills, boosts confidence, and promotes iterative learning through feedback and performance analysis.

In corporate recruitment, HR departments and hiring managers could use the platform as a preliminary screening tool. Candidates can be evaluated via automated mock interviews, which use NLP-based analysis to assess both material accuracy and communication style. The simulation not only standardizes the evaluation process, decreasing human bias, but it also saves time and costs by screening candidates prior to scheduling actual interviews.

As remote hiring becomes more common, technologies like these can provide virtual onboarding, pre-employment exams, and ongoing professional development. Real-time voice input, emotional state identification via face tracking, and adaptive questions based on performance provide a level of detail that traditional interviews cannot match.

Overall, this system closes the gap between college preparation and industry standards. It develops a highly collaborative, data-based, and intelligent platform that prepares people for the difficulties of modern job interviews, resulting in wiser hiring practices and more career-ready graduates.

CONCLUSION

The creation of the 2D Interview Panel Simulation apparatus represents a huge step forward in closing the gaps in traditional interviewing approaches. By merging interactive 2D avatars with powerful machine learning techniques like cosine similarity, TF-IDF vectorization, and BERT-based semantic analysis, this system provides candidates with a personalized, adaptable, and engaging environment in which to practice and improve their interview abilities.

The system efficiently simulates real-world interview circumstances by adapting questions to the user's chosen job and difficulty level, providing a dynamic progression from novice to expert. The incorporation of real-time feedback based on natural language understanding offers enormous value by assisting users in identifying the strengths and shortcomings in their responses. Furthermore, the interactive aspect of avatar-led interviews produces a more realistic experience that reflects the stress and flow of real-world employment interviews. Early user evaluations and comments show that utilizing the system increases confidence, engagement, and readiness, indicating that it is effective at reproducing genuine interview conditions.

Despite its revolutionary features, the system has limits. The current hurdles include a lack of nonverbal communication cues, such as facial expressions or tone analysis, as well as a need for more diversified role- and industry-specific question sets. Certain NLP models, like BERT, have high computational demands, which limit real-time performance, especially on low-resource devices.

Looking ahead, the system has the potential to expand into a more complete and scalable solution. Future upgrades could include voice and facial expression tracking, expanded role-based question banks, and more customization options based on user performance history and preferences. With further refining, the 2D Interview Panel Simulation might become a game-changing tool in both educational and business settings, nurturing better-prepared, more confident, and job-ready applicants across a wide range of industries.

REFERENCES

[1] .. T. T. ,. W. W. G. M. V. S. ,. W. M. K. ,. E. E. M. O. M. ,. K. S. R. M. J. S. R. S. K., “Guru Gedara: Smart Mathematical e-learning Platform for Grade Five Students,” INTERNATIONAL CONFERENCE ON ADVANCED RESEARCH IN COMPUTING;,” 21 February 2021.

[2] B. P. a. U. S. T. Alsubait, “A similarity-based theory of controlling MCQ difficulty," 2013 Second International Conference on E-Learning and E-Technologies in Education (ICEEE), Lodz, Poland,” 2013.

[3] D. R. C. a. S. K. Saha, “Automatic Multiple Choice Question Generation From Text: A Survey,” *in IEEE Transactions on Learning Technologies, vol. 13, no. 1, pp. 14-25, ,* 1 Jan.-March 2020.

[4] V. .. S. J. S. G. P. M. V. Mrs.V. Hemalatha, “"INTERVIEW PREPARAION,” Vols. JARIIE-ISSN(O)-2395-4396, vol. 9, no. 3,, 2023.

[5] P. V. Chintalapati, S. S. Paluri, S. S. Nikhitha, T. S. V. Nanditha, S. T. V. L. Daneswari and P. K. Sree, “Research Model For Automated Prediction And Analysis Of Job Interview Performance,” 19-20 April 2024.

[6] G. R. R. ,. A. S. K. Bijjamula Chakradhar Reddy, “AI-Powered Mock Interview Preparation,” 2025 March .

[7] M. S. ,. N. F. S. Khadijah Amira Abdul Rashid, “THE IMPORTANCE OF ZAKAT INTERVIEW PANEL: AN ANALYSIS AT UNIT ZAKAT, SEDEKAH AND WAKAF (UZSW) UiTM JOHOR BRANCH,” 09. 2024.

[8] W. X. ,. Q. W. Peng Chen, “MixedGaussianAvatar: Realistically and Geometrically Accurate Head Avatar via Mixed 2D-3D Gaussian Splatting,” December 2024.

[9] N. N. Mizuki NakajimaKaoruko ShinkawaYoshihiro, “Development of the Lifelike Head Unit for a Humanoid Cybernetic Avatar ‘Yui’ and Its Operation Interface,” 2024 January .

[10] B. P. a. U. S. T. Alsubait, “A similarity-based theory of controlling MCQ difficulty,” Vols. 2013 Second International Conference on E-Learning and E, 2013.

APPENDICES

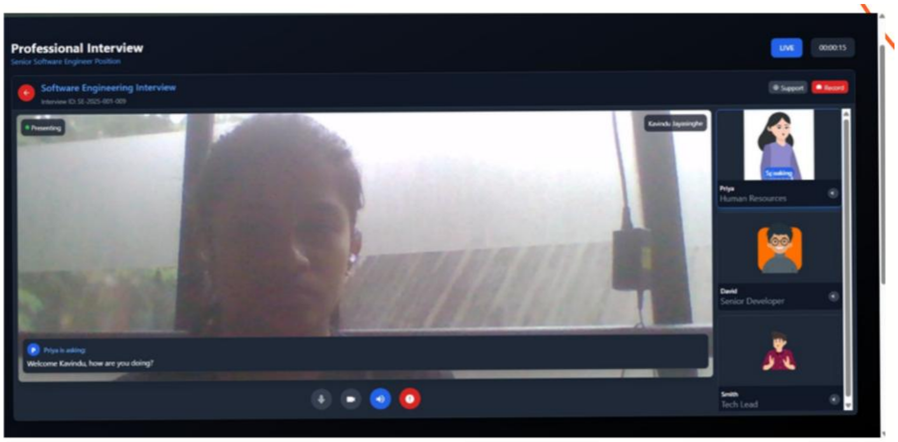

figure 7: Web Application Interview DashBoard

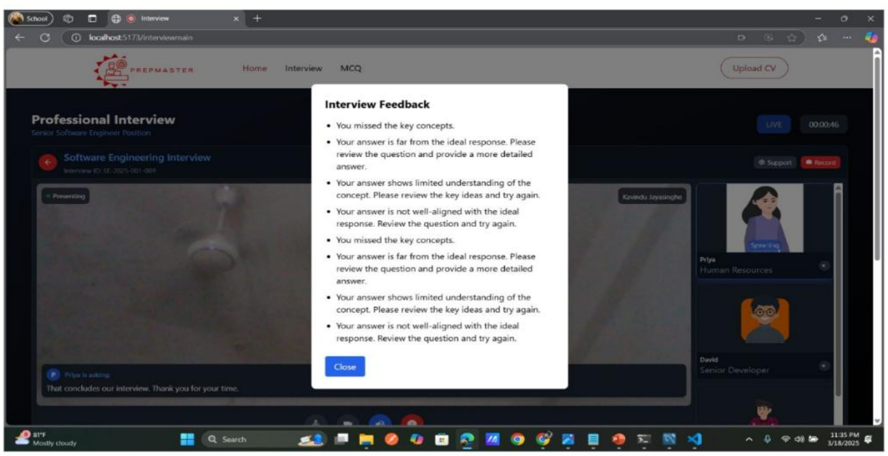

figure 8:Web Application After Interview Feedback

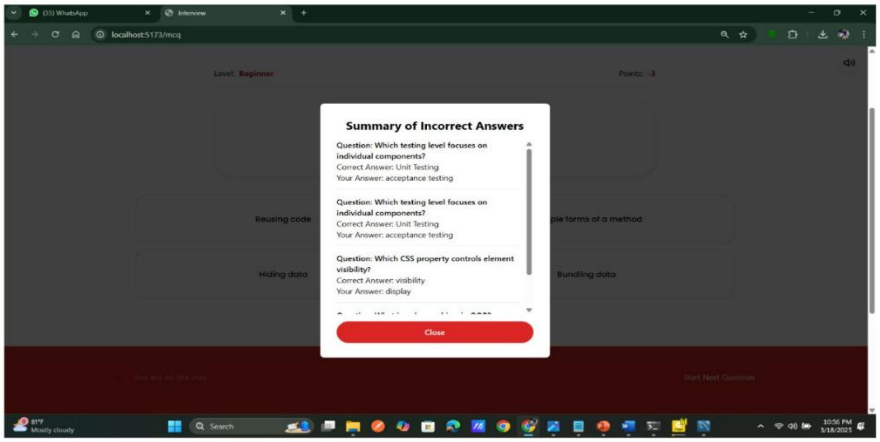

figure 9:After giving The Incorrect Answer Web Application DashBoard

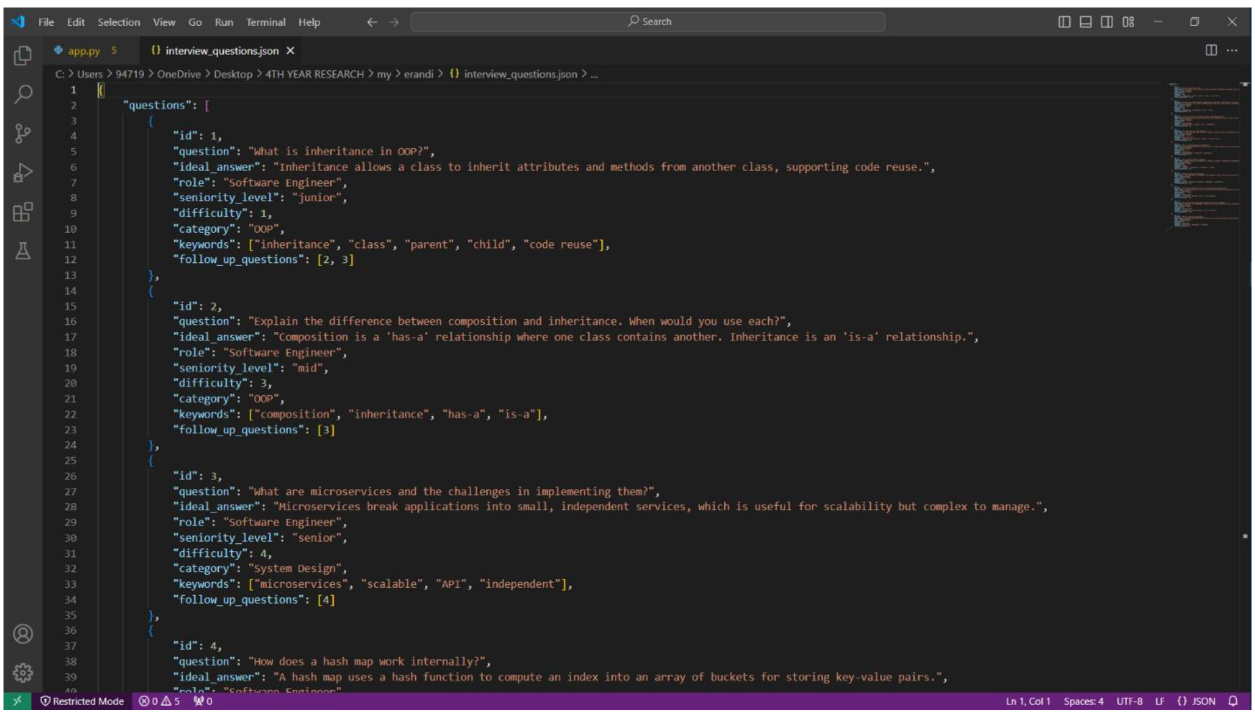

figure 10:Data Collection

```
@app.route('/api/start-interview', methods=['POST'])
def start_interview():
    data = request.json
    role = data.get('role')
    seniority_level = data.get('seniority_level')
    candidate_id = data.get('candidate_id')

    if not all([role, seniority_level, candidate_id]):
        return jsonify({'error': 'Missing required fields'}), 400

    # Create new interview session
    selector = QuestionSelector(QUESTIONS_DATA)
    questions = []
```

figure 11:Data Preprocessing 1

```python
@app.route('/api/submit-answers', methods=['POST'])
def submit_answers():
    data = request.json
    interview_id = data.get('interview_id')
    answers = data.get('answers')  # List of {question_id: X, answer_text: Y}

    if not interview_id or not answers:
        return jsonify({'error': 'Missing required fields'}), 400

    interview = Interview.query.get(interview_id)
    if not interview:
        return jsonify({'error': 'Interview not found'}), 404

    if interview.status == 'completed':
        return jsonify({'error': 'Interview already completed'}), 400
```

figure 12:Data Preprocessing 2

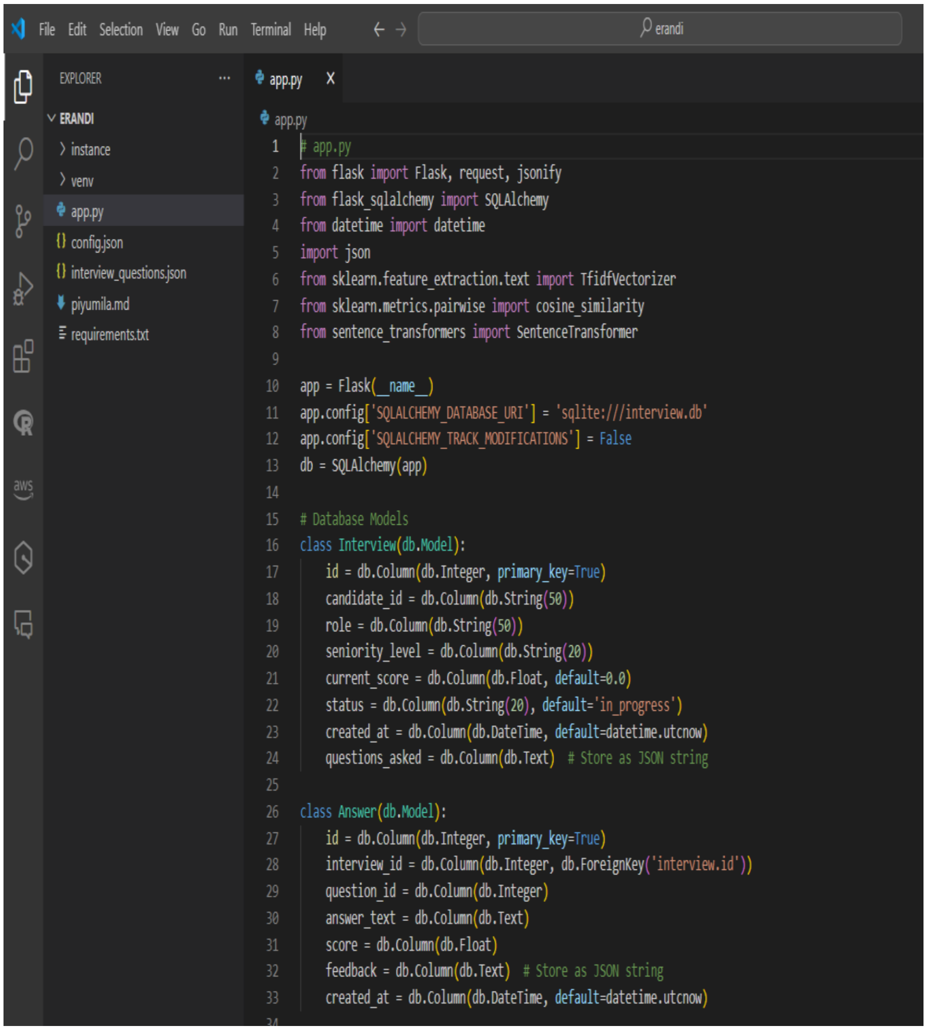

figure 13:Flask Backend

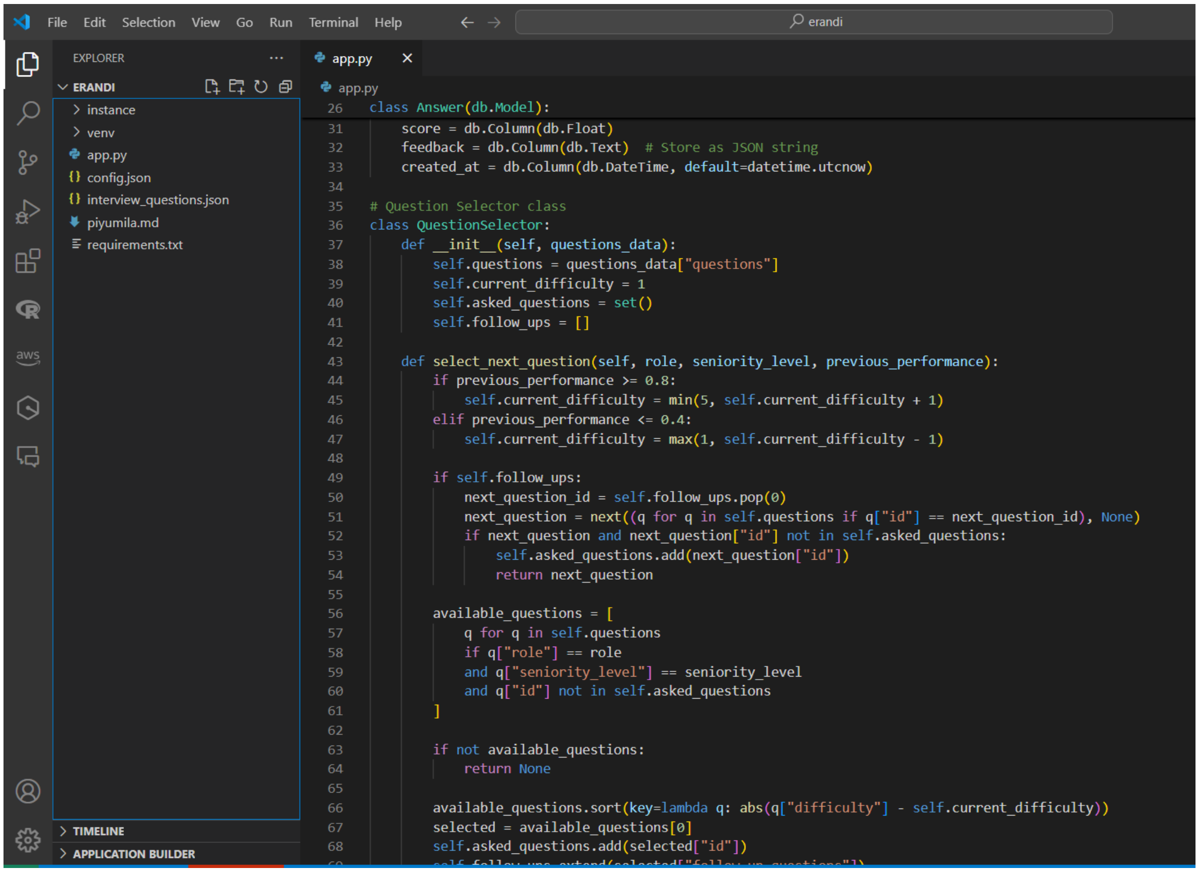

figure 14:Flask Backend 2

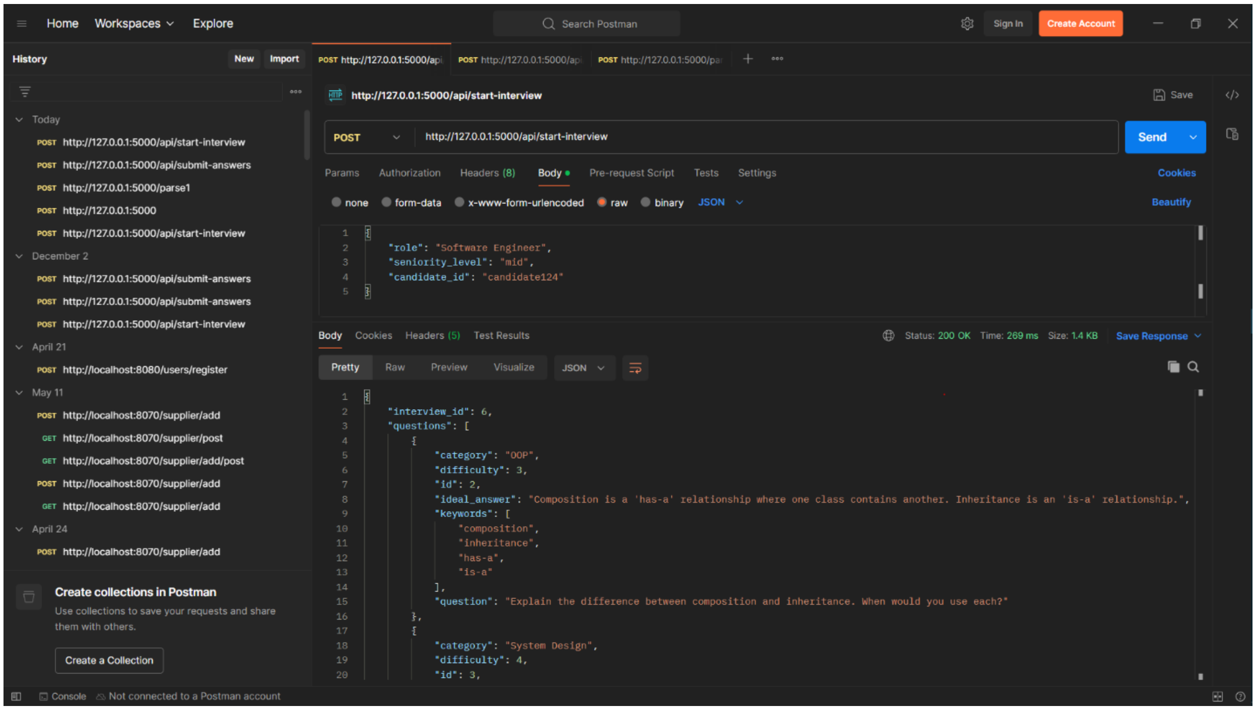

figure 15:Postman Connection