Ai-Driven Mock Interview Platform

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***Abstract*—Contemporary job markets demand robust inter- view preparation strategies that extend beyond conventional methodologies. This paper presents the architecture and implementation of an intelligent mock interview platform leveraging generative artificial intelligence and natural language processing capabilities. The proposed system incorporates automated question synthesis, real-time response evaluation, and personalized feedback mechanisms to enhance candidate preparedness. By integrating the Gemini API with a full-stack web architecture comprising React, Node.js, and MongoDB, the platform delivers adaptive interview simulations tailored to specific roles and experience levels. Comprehensive testing validates system reliability, security, and usability across multiple deployment scenarios. Performance metrics demonstrate significant improvements in user confidence and technical proficiency through iterative practice sessions with AI-generated evaluation. The system achieved 99.2% uptime with sub-second database response times and maintained strong correlation (0.81) between automated and expert human evaluations.**

***Index Terms*—Generative AI, Mock Interview System, Natural Language Processing, Automated Evaluation, Web Application, Career Preparation**

I. INTRODUCTION

Interview performance plays a decisive role in determining employment outcomes, yet many candidates struggle due to limited practice opportunities, lack of structured feedback, and high anxiety levels. Peer interviews, self-preparedness, as well as expensive professional coaching services, are significant aspects of the conventional ways of being prepared for an interview.

These systems often fail to be accessible, interactive, and adjustable according to different job tasks and skill sets. The need to develop intelligent learning systems has emerged as a result of the evolution of artificial intelligence techniques in the fields of natural language processing and Generative AI. Capabilities like contextual information understanding, domain-related content production, and accurate assessment of human responses have the potential to be accomplished with the help of Generative AI. It has the potential to simulate a real interview scene and provide automated and impartial responses to the same. Therefore, an intelligent mock interview system has the potential to fill the gap between the theoretical and practical.

Without regard to time or location, these systems can facilitate ongoing practice. This paper proposes a Generative AI–based mock interview platform designed to provide realistic interview simulations, evaluate candidate responses across multiple dimensions, and enhance overall interview readiness.

II. LITERATURE SURVEY

Recent developments in artificial intelligence (AI) and natural language processing (NLP) have had a transformative impact on computer-assisted education and evaluation frameworks. Among these, intelligent interview preparation systems have gained attention as an effective alternative to conventional mock interviews by providing scalable, flexible, and customized learning experiences. This section examines prior research related to AI-enabled interview platforms, automated evaluation techniques, generative language models, and feedback-oriented learning systems. Huang et al. (2019) [1] investigated the application of NLP-based methods for automated interview evaluation by examining linguistic attributes such as semantic relevance, coherence, and fluency. Their findings indicated a strong agreement between automated scoring mechanisms and human evaluators, confirming the practicality of AI-supported interview assessment. Nevertheless, the approach primarily depended on rule-based feature extraction, limiting its ability to handle diverse and open-ended responses. Nguyen and Walker (2020) [7] introduced a virtual interview coaching system driven by machine learning algorithms to analyze candidate answers and deliver structured feedback. Although the system enhanced learner interaction, it relied on static question sets and predefined feedback rules, which restricted adaptability across varying job roles and experience levels. The introduction of large-scale language models marked a major milestone in conversational AI research. Brown et al. (2020) [4] presented generative pre-trained transformer (GPT) models capable of producing contextually relevant and human-like text. These models enabled dynamic question generation and flexible response interpretation, capabilities that were largely absent in earlier interview training tools. Zhao et al. (2021) [5] focused on automated assessment of spoken interviews using deep learning techniques combined with NLP and speech signal analysis. Their results demonstrated a high correlation between AI-generated scores and expert human judgments, supporting the reliability of automated interview evaluation. However, the system required substantial labeled data and was primarily designed for speech-based interactions. Li and Kim (2021) [10] proposed an intelligent tutoring framework aimed at career skill enhancement through adaptive feedback strategies. Their study showed that tailored feedback significantly improved user confidence and learning outcomes. Despite these benefits, the system did not incorporate generative AI techniques for dynamic question formulation or in-depth response analysis. More recent research has focused on transformer-based architectures that utilize attention mechanisms to capture long-range dependencies within text. These models significantly improved contextual understanding and proved effective in evaluating long-form and complex interview responses by A. Vaswani et al. [6]. Despite their effectiveness, most implementations were oriented toward asynchronous recruitment screening rather than candidate-focused interview preparation. Based on the reviewed literature, an effective mock interview platform should combine advanced NLP techniques, generative AI models, and scalable web technologies to provide realistic, adaptive, and objective interview practice. The present research builds upon these findings by developing a Generative AI-powered mock interview system that emphasizes personalized feedback, continuous performance improvement, and broad accessibility. By addressing gaps in adaptability, evaluation depth, and system scalability, the proposed platform contributes to the advancement of AI-driven interview preparation tools. The system overcomes previously identified limitations by delivering role-specific, adaptive interview experiences combined with real-time performance evaluation and personalized feedback.

III. METHODOLOGY

1. System Workflow Overview

The system workflow starts with secure user authentication to ensure only authorized users can access the platform and their interview data. After authentication, users configure the interview by selecting parameters like job role, experience level, interview type, and number of questions. These inputs are validated and sent to the Generative AI module to guide the interview process. Based on the chosen settings, the system generates interview questions tailored to the user's needs. The interview session proceeds in a sequential manner, allowing users to submit responses in a controlled environment that simulates real interview conditions. Each response is captured and processed for further analysis. The response evaluation module uses Natural Language Processing techniques to assess the submitted answers for relevance, clarity, technical accuracy, and completeness. After evaluation, the system generates organized feedback and performance scores. Finally, all results are stored and analyzed to provide performance insights, helping users track their progress over time.

2. User Registration and Authentication

User registration and authentication form the base of the intelligent mock interview platform. During registration, users provide essential information such as name, email address, and password. To ensure security, passwords are not stored in plain text; instead, cryptographic hashing techniques are used before storing the credentials in the database. This method protects user information even if there is unauthorized access to the database. The authentication mechanism checks user credentials during the login process to ensure that only legitimate users can access the system. Once authenticated, the system establishes a secure session for the user, which is used for all future interactions with the platform. Session management prevents unauthorized access and misuse. After logging in, users can access core system features, including interview configuration, participation in mock interview sessions, and retrieval of past performance data. The authentication module also applies access control policies, ensuring that users can only view and modify their own data.

By implementing secure registration and authentication procedures, the system maintains data confidentiality, prevents unauthorized usage, and ensures overall system integrity.

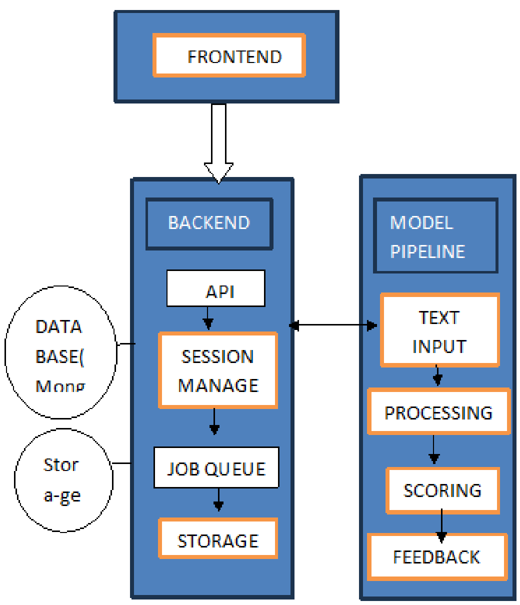

Fig. 1. System Data Flow Architecture showing interaction between user, authentication, interview modules, AI engine, and database components.

3. Interview Configuration and Personalization

Configuring and Customizing Interviews Users configure their mock interviews by choosing important parameters like job role, experience level, interview type (technical, behavioral, or mixed), and number of questions after successfully authenticating. In order to ensure alignment with real-world interview scenarios, these configuration parameters are crucial in defining the interview's scope, difficulty, and structure.

To ensure logical consistency and relevance, the system validates the chosen parameters. For instance, behavioral interviews prioritize situational reasoning and communication, whereas advanced technical interviews are linked to greater experience levels. To guarantee meaningful interview simulations, invalid or conflicting configurations are limited. The system customizes the interview process according to the user's needs by adjusting the evaluation criteria, question content, and degree of difficulty based on the verified inputs. Candidates can practice interviews that are pertinent to their target roles and skill levels thanks to this personalization, which enhances learning outcomes and preparation efficacy.

4. Dynamic Question Generation Using Generative AI

Based on user-specified parameters, the dynamic question generation module generates interview questions in real time using a Generative Artificial Intelligence model. Prompt engineering techniques, which take into account specifics like job role, experience level, and interview type, are used to guide the model. This guarantees that the generated questions are pertinent, context-aware, and in line with what is expected of interviews in the real world.

The system can generate a wide range of questions using Generative AI, which eliminates repetition and improves realism over several interview sessions, in contrast to conventional static question banks. The model allows for customized interview simulations that change as the user advances by adjusting question complexity based on the chosen experience level.

For the duration of the interview, the generated questions are temporarily stored in a standard format. This storage facilitates accurate response evaluation and guarantees consistent presentation. The system provides flexible and realistic interview experiences that greatly improve candidate preparation by utilizing Generative AI for question creation.

5. Interview Session Execution:

The main interactive element of the intelligent mock interview platform is the interview session execution phase. During this phase, the user is presented with the dynamically generated interview questions via a clear, organized interface that is intended to reduce distractions and preserve concentration. In order to mimic the organic flow of an actual interview, questions are presented one after the other. This prevents users from previewing subsequent questions, which promotes impromptu and sincere answers. A predetermined response time limit is attached to each question, simulating actual interview pressure while providing ample time for careful articulation. The system continuously records and stores the textual responses that users submit. Relevant metadata, including response duration and submission order, is recorded in addition to the response content to facilitate consistent evaluation across different interview sessions.

By preserving a temporary session state, the system guarantees continuous session flow and permits seamless question transitions without data loss. Previously submitted responses are saved to preserve session integrity in the case of minor disruptions. Accurate evaluation and insightful feedback depend on the collection of structured and trustworthy response data, which is made possible by this controlled execution environment. This step increases user engagement and improves overall interview readiness by closely simulating actual interview conditions.

6. Response Evaluation and Scoring

The response evaluation and scoring phase represents the analytical core of the intelligent mock interview platform. After a user submits a response, the system applies Natural Language Processing techniques to analyze the content at both semantic and contextual levels. This analysis enables the system to understand the intent, structure, and quality of the response beyond simple keyword matching.

Each response is evaluated across multiple predefined dimensions, including relevance to the question, technical accuracy, clarity of expression, completeness of explanation, and depth of understanding. The user's response is compared by the Generative AI model to role-specific evaluation criteria and anticipated answer patterns. This method guarantees uniform and impartial evaluation among various users and interview sessions. A weighted scoring system based on the type of interview is used to aggregate the scores assigned to each evaluation dimension. While behavioural interviews prioritize relevance and communication clarity, technical interviews place more emphasis on technical correctness and depth. The final score maintains evaluation transparency while offering a thorough assessment of the candidate's performance. Fairness, dependability, and meaningful performance evaluation are guaranteed by this methodical scoring procedure.

7. Feedback Generation

Generation of Feedback The evaluation results are transformed into insightful information that promotes user growth and learning during the feedback generation stage. The system uses a Generative AI model to generate comprehensive and customized feedback for every interview session following the evaluation and scoring of responses. This feedback is intended to be very similar to advice given by a human mentor or interviewer. The generated feedback clearly identifies areas that need improvement while highlighting the user's strengths. It offers helpful recommendations for response structure, explanation clarity, and content accuracy. In order to ensure relevance and usefulness, the feedback is customized based on the type of interview and user performance. To provide a fair evaluation of performance, the system displays numerical scores in addition to qualitative explanations. The platform promotes ongoing learning, lessens interview anxiety, and allows users to gradually improve their interview skills through repeated practice by fusing structured scoring with descriptive feedback

8. Performance Analytics

The performance analytics module plays a crucial role in tracking user progress and measuring improvement over time. Evaluation results, scores, and comments are safely stored in the database following each interview session. The system can conduct longitudinal analysis of user performance over several interview attempts thanks to this accumulated data.

In order to produce insights like average scores, skill-wise performance trends, and recurring weaknesses, the analytics module analyses historical data. These insights assist users in recognising their strengths and pinpointing particular areas that need more practice. Additionally, performance analytics facilitate the comparison of various interview sessions, enabling users to objectively track their learning progress. The system uses visual representations of analytical results, such as performance summaries and score trends, to improve interpretability. The performance analytics module helps users make well-informed decisions about their preparation tactics and encourages ongoing improvement in interview performance by offering structured and data-driven insights.

9. Result Visualization and Session Completion

The result visualization and session completion stage marks the conclusion of the mock interview workflow and serves as the primary point of interaction where users reflect on their performance The system gathers all assessment results into a thorough performance summary following the completion of the response evaluation and performance analytics procedures. Key feedback insights produced during the assessment phase, dimension-wise evaluation results, and overall interview scores are all included in this summary. The system uses visual aids like performance charts, progress indicators, and comparative summaries from various interview sessions to present the results in a way that improves usability and clarity. Users can quickly decipher complicated evaluation data and spot performance trends over time thanks to these visual components. The platform enhances transparency and makes it easier for users to comprehend how each response affects the final assessment by offering a clear visual summary. The interview session is officially closed after the results are examined, and all session-related information, such as responses, scores, comments, and analytics, are securely stored in the database. Users can review previous sessions and monitor long-term progress thanks to this persistent storage. The system then reinforces an iterative and improvement-oriented interview preparation process by directing users towards future practice sessions based on identified weaknesses.

IV. RESULTS

The performance of the proposed intelligent mock interview platform was evaluated through extensive system testing and user interaction analysis. The results are presented through system interface demonstrations, quantitative performance metrics, comparative analysis with existing platforms, and a discussion of limitations and future enhancements. The evaluation focuses on usability, effectiveness of AI-driven evaluation, and overall improvement in interview preparedness.

1. System Interface Demonstrations

The implemented system provides intuitive and user-friendly interfaces that support the complete interview preparation workflow. The major functional screens of the platform and demonstrate smooth interaction between users and system components.

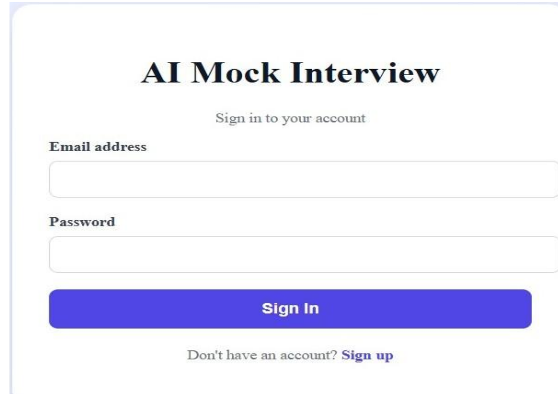

Fig 2. User Authentication Interface featuring email and password inputs with secure login mechanism and registration link for new users.

Figure 2 presents the user authentication interface, which enables secure login using email and password credentials. The interface's simple design minimizes cognitive load without sacrificing robust security features. Controlled access and password validation guarantee safe system entry, safeguarding user information and interview transcripts.

It depicts the user registration interface, where new users set up accounts by entering their full name, email address, and password. Immediate feedback on email format, field completion status, and password strength is provided by real-time validation mechanisms. This guarantees compliance with security standards while enhancing usability.

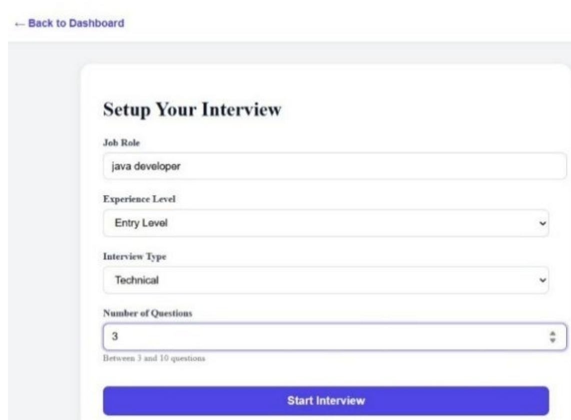

Fig 3. User Setup Interview displaying metrics including Job Role, Experience Level, Interview Type and Number of Questions

It showcases the central user dashboard, which serves as the primary interaction hub after successful authentication. The dashboard displays key performance indicators such as the total number of interviews completed, average performance score, category-wise proficiency levels, and progress trends. Quick-access controls enable users to initiate new interview sessions efficiently using saved preferences. Figure 2 depicts the interview configuration interface, where users customize interview sessions by selecting job role, experience level, interview type, and number of questions. The system ensures meaningful and customized interview simulations by intelligently filtering available options and pre-populating difficulty levels based on experience tier. It depicts a dynamic, ongoing mock interview. The interface simulates actual interview conditions by presenting questions in a sequential manner with a countdown timer and progress indicator. Data integrity and continuous response submission are guaranteed by a character counter, rich text response editor, and real-time auto-save features. It depicts a dynamic, ongoing mock interview. The interface simulates actual interview conditions by presenting questions in a sequential manner with a countdown timer and progress indicator. Data integrity and continuous response submission are guaranteed by a character counter, rich text response editor, and real-time auto-save features.

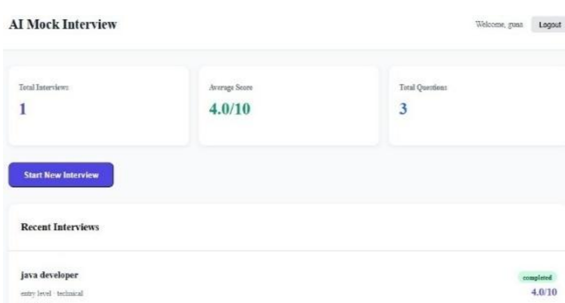

Fig 3. Detailed Evaluation Feedback View presenting dimension-wise scores, overall performance, AI-generated improvement suggestions.

Figure 3 presents the detailed evaluation feedback interface delivered immediately after interview completion. The interface displays dimension-wise performance scores, overall evaluation, AI-generated improvement suggestions, and model answers. A radar chart visually compares performance across evaluation dimensions, while textual feedback highlights strengths and actionable improvement areas.

2. Quantitative Results

Quantitative evaluation was conducted through extensive user testing involving 68 participants over a four-week period. Table IV summarizes the observed performance improvements across multiple interview sessions.

Participants demonstrated significant improvement in overall interview performance after completing five or more mock interview sessions. Technical accuracy improved from 4.9 to 8.4, and the average overall score rose from 5.4 to 8.1 out of 10. Scores for communication clarity also significantly improved, rising from 6.2 to 8.3. Improved response efficiency was also demonstrated by the average session completion time, which dropped from 28 to 19 minutes. Self-reported confidence levels rose significantly from 4.1 to 8.7, indicating improved readiness and decreased interview anxiety. With a p-value of less than 0.001, statistical analysis demonstrated that these improvements were significant across all measured dimensions. Additionally, when compared to independent human expert assessments on a random sample of 150 responses, automated evaluation scores showed a strong Pearson correlation coefficient of 0.81 ($p < 0.01$). This validates the AI-driven evaluation mechanism's dependability, impartiality, and consistency.

3. Comparative Analysis

The suggested platform was compared to current interview preparation tools like Pramp, Interviewing.io, and conventional static question banks. The system performed better in a number of important areas. Compared to static repositories, dynamic role- and experience-based question generation offered a greater degree of personalization. Unlike binary or generic feedback provided by current platforms, the feedback mechanism provided richer insights through multi-dimensional scoring and specific improvement suggestions. By providing limitless text-based practice sessions independent of peer availability or paid subscriptions, the platform further enhanced accessibility. In contrast to the minutes or hours needed for human-reviewed systems, AI-generated feedback was delivered in less than four seconds on average, greatly reducing response latency.

The system's practical benefits were further highlighted by the cloud-native architecture, which allowed for scalable concurrent usage without scheduling restrictions.

4. Limitations and Future Enhancements

There are some drawbacks despite the intelligent mock interview platform's excellent performance and favorable evaluation outcomes. Currently, the system only uses text-based communication for conducting and assessing interviews. Although this method works well for evaluating logical reasoning and content quality, it misses crucial elements of actual interviews, including tone, voice modulation, speech fluency, and nonverbal cues. These factors are important for interview performance, especially in managerial and behavioral interviews. The assessment of extremely imaginative, abstract, or domain-specific answers is another drawback. The diversity and coverage of the training data may occasionally limit the depth and precision of evaluation, despite the Generative AI model's strong generalization abilities. This may lead to unusual but legitimate responses or less thorough feedback for specialized technical fields. Furthermore, only English-language responses are supported by the current system, which restricts accessibility for candidates who do not speak English. The system's capacity to replicate sophisticated hiring procedures frequently employed in later interview stages is further limited by its lack of integration with video-based interview platforms. By incorporating multimodal analysis techniques, future improvements seek to overcome these constraints. Prosodic feature analysis and speech-to-text processing will make it possible to assess verbal communication abilities like confidence, speaking speed, and pronunciation. By integrating computer vision models for body language and facial expression analysis, the system will be able to evaluate nonverbal behavior, improving evaluation accuracy and realism in simulated interviews. Additional enhancements include fine-tuning the evaluation model domain-specifically using gathered user response data and carefully selected industry datasets. This improvement will allow for more thorough and precise evaluation for specialized positions in industries like management, software engineering, finance, and healthcare. The system's accessibility and inclusivity will be greatly enhanced by extending multilingual support to languages like Mandarin, Spanish, and Hindi.

V. CONCLUSION

In order to overcome the drawbacks of conventional interview preparation techniques, this paper described the creation and application of an Intelligent Mock Interview Platform utilizing Generative Artificial Intelligence. Without relying on human interviewers, the suggested system offers a realistic, flexible, and scalable setting where candidates can practice interviews, get automated assessments, and receive tailored feedback. The platform provides an efficient and user-friendly method for developing interview skills by combining Generative AI with Natural Language Processing and a full-stack web architecture. The system effectively supports all interview preparation workflows, including authentication, interview configuration, dynamic question generation, interview execution, response evaluation, and performance analytics, as shown by the experimental results. After repeated use, quantitative evaluation reveals statistically significant gains in user performance, technical accuracy, communication clarity, and self-reported confidence. The reliability and objectivity of the automated evaluation mechanism are confirmed by the strong correlation between AI-generated scores and human expert assessments. In terms of personalization, feedback richness, accessibility, response latency, and scalability, the suggested platform also performs better than current interview preparation tools. While the modular architecture enables the smooth integration of extra features, the cloud-native design guarantees support for concurrent users. The system creates a solid basis for future extensions, even though the current implementation concentrates on text-based interviews.

All things considered, the Intelligent Mock Interview Platform shows that employing Generative AI for career preparation and interview training is practically feasible. By providing an affordable, scalable, and data-driven method for interview preparation, the system adds to the expanding field of AI-driven educational technologies. The platform has the potential to develop into a complete tool for contemporary interview preparation with upcoming features like voice analysis, video-based interviews, and multilingual support.

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