



AI – Powered Mock Interview

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Abstract. What shapes an interview isn't just the question but the way each moment unfolds. With a mock interview system, a job seeker gets to experience a realistic environment where they can practice and enhance their interviewing abilities. Traditional mock interviews are usually conducted by human interviewer, career coaches, mentors, or people who, based on their experience and knowledge of the industry, will ask questions and provide feedback. The fact that candidates get to interact with a person themselves allows them to work on communication skills and develop more confidence to respond naturally to how others act. These can be tailored according to the job role and specific industry, hence giving an avenue for tailor-made practice. The opportunity to interact with a real person creates pressure like what the candidate may feel during an actual interview, hence helping them manage stress and perform better. In a mock interview, the candidate responds to questions about past experiences, technical knowledge, or how they would handle a certain situation. The interviewer then observes and assesses different aspects, such as clarity in speaking, the level of confidence, body language, and substance in the answers given. They then provide immediate or in-depth feedback right after the session, highlighting strengths and possible areas for improvement. Personalized feedback is helpful because it is based on real professional experience and pragmatic comprehension. Traditional mock interviews are efficient at capturing emotional aspects and adapting to the different ways one could ask a question; however, they are time-consuming and depend on the availability of an interviewer. They are generally appreciated for being interactive in nature and realistically simulating real-life job interviews. Conclusion A no-AI mock interview platform is the one that relies on experts in order to create an interactive environment that nurtures the preparation of job seekers in terms of real-life interviews. This approach becomes specifically efficient for those who need extensive and customized coaching, while laying great emphasis on soft skills, natural communication, and field-related situations.

Keywords: Mock interview, traditional interview practice, human feedback, multimodal, interview preparation, job interview skills.

1 Introduction

The AI interview simulator creates a preparatory environment for a job candidate to experience the type of questions that are most likely asked in their role. Based on experience, skills, and the target job role, the system generates relevant questions for interviews. The realistic simulation of interviews offered through the platform, with the option to record video or audio responses, helps users prepare effectively for face-to-face and online interviews. For example, advanced technologies analyze the clarity and confidence of the candidate's speech and analyze them using linguistic and speech-based features. The results are instantaneous and presented in a structured manner to provide clear insights into their strong points, as well as elements that need to be enhanced. Here, there are not only technical and behavioral questions but also scenario-based questions. One of the major advantages is personalized and fair evaluation. It performs detailed analysis of responses and underlines a variety of attributes such as filler words, pauses, and the relevance of answers. It also offers progress tracking, which helps candidates track their progress, it provides a better understanding of themselves and encourages them to learn more. Most of the platforms support multiple languages and are sensitive to many accents, so the mock interview can be accessible to users worldwide. The possibility to schedule at any time and to repeat the practice makes users independent of human coaches. Special features like performance scores and achievement badges sustain candidates' interest and motivate them to improve their performance. This system ensures fairness in the use of data because, through it, progress is continuously tracked over time. Such practice is particularly needed for individuals in remote areas or underrepresented regions to access structured interview practice regardless of location or wealth. AI driven mock interviews provide increased access to career preparation through individual and group training that helps students, job seekers, and professionals. Users become comfortable with the interview process through repeated practice, leading to increased confidence levels and, finally, success in interviews.

2 Literature Review

Studies on AI-powered mock interviews show that these systems have advanced significantly and are deemed very effective. That is why the owners of these platforms, as well as researchers and developers, created them in such a way as to simulate real interview situations, which further allows candidates to become better prepared for actual interviews. The first results in this area proved that AI technologies can create interview questions personalized for the candidate profile. The platform uses NLP and machine learning technologies that assess the verbal answers provided by users and give instant feedback on their communicational skills and technical know-how [1][4]. As noted by several authors, an AI-Powered mock interview possesses numerous sophisticated characteristics, among which is the ability to recognize emotions based on facial expression analysis [2][3][5].

These tools were used to give one an idea about the confidence level and emotional stability of a candidate when interviewed. The real-time analysis was aimed at making candidates more self-aware so that they would avoid exhibiting nervousness and exhibiting positive body language instead. This speech analysis was used to assess the overall voice modulation, tone, and pace that led to building overall interview preparation. The platforms were identified to be accurate in identifying the emotional states and confidence levels and thereby providing actionable insights, which could be used by candidates to improve performance [4].

Additional research highlighted that these systems are scalable, accessible, and inexpensive solutions compared to conventional mock interview solutions. They do not suffer from such limitations as scheduling or location constraints, and as such, they enjoyed wide popularity among active job seekers and students. Several reviews also proved that the candidates using AI- enabled platforms felt more confident and well prepared with enhanced interview skills, which were shown in their performance at actual interviews. Overall, the literature reviewed supports that AI- powered mock job interviews can be effective, transformative tools in boosting one's preparation, lowering anxiety levels, and thus enhancing success rates in real job interviews.[1][4]

3 Body: (Proposed methodology/ Design and implementation of proposed system)

The new interview system uses intelligence to help people practice. It looks at what people say in two ways: by understanding the words they use and by listening to how they speak. The system takes what people say and does things with it: it figures out what they are saying, looks at the words they use, finds the important parts, and then gives them some feedback on how they did. The interview system is really good at helping people get better at talking about themselves. The system uses intelligence to make the interview feel more real.

3.1 Speech – to – text Processing

Users' responses are first turned into text using an Automatic Speech Recognition (ASR) system. The ASR module changes audio input into written form while keeping timestamps, which allows for matching between text and speech [6][8].

Let:

- $A(t)$ = input audio signal
- T = transcribed text

$$T = \text{ASR}(A(t))$$

The timestamps are used later to compute pause durations and speech rate.

3.2 Natural Language Processing

To evaluate the semantic quality of responses, we employ a transformer- based language model (e.g., BERT or LLM-based prompting via Gemini API) [7].

Text Preprocessing

- Tokenization
- Stop-word removal
- Lemmatization

Semantic Similarity

The candidate's response is compared with expected answers using embedding similarity:

$$\text{Score}_{\text{semantic}} = \text{cosine} (E_{\text{user}}, E_{\text{reference}})$$

Where:

- E_{user} = embedding of user response
- $E_{\text{reference}}$ = embedding of ideal answer

Relevance Classification.

A classifier determines whether the answer is relevant to the question:

- Model: Fine- tuned transformer classifier
- Output: Relevant/ Irrelevant score

3.3 Speech Feature Extraction

To assess communication quality, prosodic and fluency features are extracted from the audio signal.

Pause Detection

Pauses are identified using silence thresholds:

$$\text{Pause Duration} = t_{\text{silence_end}} - t_{\text{silence_start}}$$

Speech Rate.

$$\dots \quad \text{Speech Rate} = \frac{\text{Number of words}}{\text{Total Speaking Time}}$$

Filler Word Detection.

A rule – based + NLP hybrid approach is used:.

- Dictionary of filler words: {"um,"uh", "like", "you know"}
- Frequency count normalized by total words.

$$\text{Filler Score} = \frac{\text{Filler Words Count}}{\text{Total Words}}$$

3.4 Feedback and Scoring Engine

A weighted scoring model combines multiple features:

$$\text{Final Score} = w_1. \text{ Semantic} + w_2. \text{ Relevance} + w_3. \text{ Fluency} + w_4. \text{ Confidence}$$

Where:

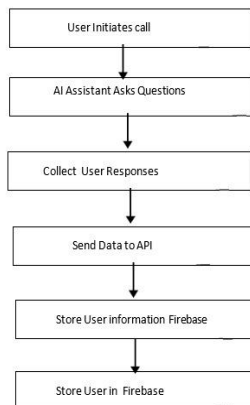
- W_i are empirically tuned weights.

The system generates feedback based on thresholds.

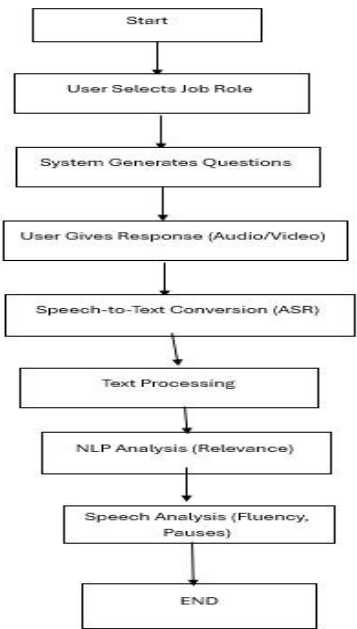
- High Filler usage – “Reduce Filler words “
- Low semantic score- “Improve content relevance”
- Long Pauses- “Work on fluency”

3.5 Design and implementation of proposed system

Authentication flow



Flowchart of Proposed System



4 Result Analysis

Table 1. Evaluation Metrics of the AI – Powered Mock Interview

Metric	Before System	After System	Improvement
Semantic score	0.61	0.78	+27%
Fluency score	0.58	0.74	+27%
Confidence score	0.55	0.72	+31%
Filler word reduction	18%	8%	-10%
Average Response Time	2.3sec	1.5 sec	faster

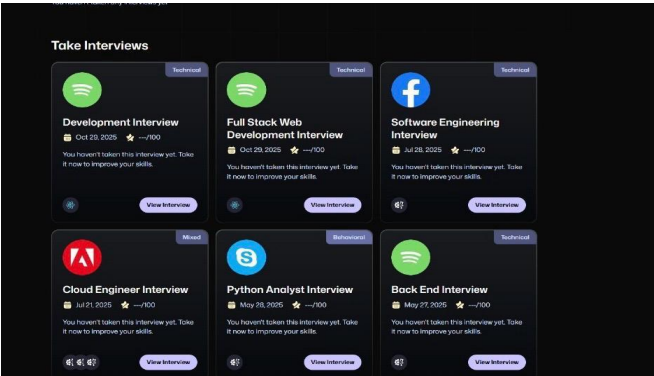


Fig. 1. The figure shows the dashboard of the interview preparation system, including multiple interview categories such as software engineering, cloud engineering, backend development, and behavioral interviews.

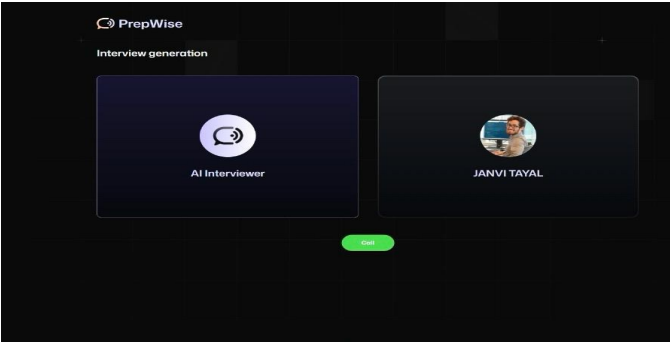


Fig. 2. This figure shows virtual mock interview interaction screen

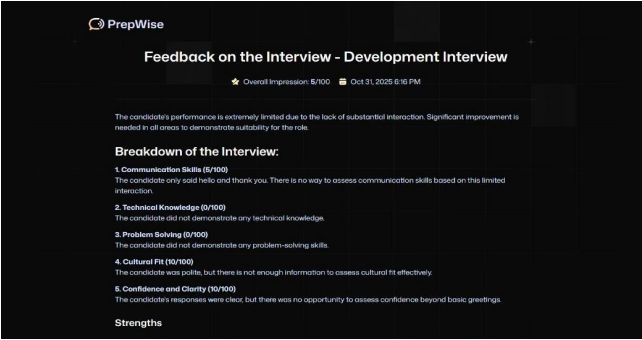


Fig. 3. This Figure Shows Candidate Skill Evaluation and Feedback System

5 Future work and Enhancements

The AI Mock Interview platform can increase the immersive Ness, engagement and realness of the user experience in future development. Among the improvements, scaling of the dataset from which the questions are generated could be done to offer more variety and even industry specific, job-specific, or skill-specific questions. The system can also be enhanced to include multi-modal assessments that integrate voice, tone, facial expression, eye movement, and gesture analysis to make the evaluation even more human-like, besides just analyzing the content of the verbal communication. Realistic interaction with the interviewer could be achieved by incorporating adaptive interview flows, through which the follow-up questions and degrees of difficulty in questioning would adjust in real-time based on the responses that the user makes. Incorporating mock panel interviews and scenario-based role-playing exercises would also help users develop problem solving and leadership skills, since it would train them on some of the more advanced and complex questions of the behavioral and situational varieties. By incorporating a variety of gamification techniques, such as achievements, scoreboards, and winning streaks, in addition to other social features that would allow for peer feedback after practicing, this would enhance the motivation and overall engagement with the tool. Adding more languages featuring voices and accents would improve tool accessibility and help the user's fluency and clarity. Lastly, if this were integrated with resume parsers and job posting portals, then practice sessions could be made more realistic, providing specific role-based practice interviews to users. Altogether, the objectives of these would be to make the tool more inclusive, personalized, and help users develop technical and soft skills necessary in numerous professional contexts [9][10].

6 Conclusion

This research paper designed and implemented a mocked interview training platform that focuses on the enhancement of technical and interpersonal skills through an interactive immersion system of a virtual environment. The system integrates a complete stack including Next.js, React, Tailwind CSS, Clerk, PostgreSQL, and Drizzle ORM, coupled with the AI-driven question generator based on the Gemini model, and develops a novel interrogation training tool that is safe, systematized, and adaptable. The system evaluates user progress and improvement in communication and analytics problem-solving through the collection of audiovisual recordings, which are then transcribed, and system feedback is generated. During the development process, the following shortcomings with respect to the AI became more apparent: communication soft detection, non-verbal speech disfluencies, narrow reach, and depth of questions and answers. This forms a basis for the need for further advances in the development of AI behavior analysis, automatic question rotation, interdisciplinary and game-based learning approaches, more languages, and simulated group interviews to ensure an all-rounded experience for the users. Overall, the platform has achieved a huge stride in improving its technology for interviews,

bridging the gap between conventional methods and the possibilities of technological learning. It is our belief that our unique integration will surely assist candidates not only in answering questions but in gaining confidence and composure. By building upon intelligent feedback, self assessment, and user experience as the foundation of our systems. We have plans to come up with even more interesting developments related to AI tools for career growth, which we think could help scale up many careers across different industries in preparing the next generation of workers. It is one of the collaborations made with other organizations and institutions interested in developing their career development tools by means of artificial intelligence.

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