



# Palm Model-Based Mock Interview Platform For Precision Career Development And Success

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**Abstract:** This paper presents the design, development, and evaluation of an intelligent mock interview platform aimed at improving career readiness through real-time, AI-driven simulations. Leveraging Google's Gemini (PALM) large language model, the system dynamically generates domain-specific interview questions and evaluates user responses based on contextual relevance, fluency, and delivery. Built using JavaScript, Tailwind CSS, Firebase, and WebRTC, the platform delivers an immersive, role-based experience simulating real-world interviews. Users select a job role to receive customized sessions, during which their audio or video responses are analysed in real time. Gemini's semantic understanding enables automated feedback across articulation, content depth, confidence, and role alignment, with session data stored securely in Firebase for review and iterative learning. The architecture comprises a user interface layer, an AI services layer powered by Gemini APIs, and a data services layer. Evaluation with 75 participants from fields such as software engineering, marketing, and data science showed a 38% improvement in performance over three sessions, validated through both automated and expert assessments. User feedback emphasized the platform's realism and adaptability. This study demonstrates the effectiveness of large language models in enhancing communication skills and proposes future enhancements including emotion analysis, multilingual support, and longitudinal impact studies.

**Index Terms - Mock Interview, Gemini PALM API, Real-time Feedback, Career Development, Audio-Video AI, Firebase**

## I. INTRODUCTION

The transition from academic learning to professional success is increasingly determined by an individual's ability to perform well in job interviews. Beyond technical expertise, employers prioritize candidates who can articulate their thoughts clearly, demonstrate critical thinking under pressure, and align their responses with organizational values. However, traditional interview preparation methods, such as self-practice, coaching sessions, and static question banks, often fail to replicate the dynamic and unpredictable nature of real interviews. This gap creates a pressing need for intelligent, adaptive platforms that can offer realistic practice environments tailored to individual career goals.

Recent advancements in Artificial Intelligence, particularly the emergence of large language models (LLMs) like Google's Gemini PaLM, have opened new possibilities for personalized learning experiences. These models possess sophisticated capabilities in natural language understanding, contextual dialogue generation, and semantic evaluation, making them ideal for simulating real-world communication scenarios. Leveraging this technological evolution, the present work proposes a novel AI-powered mock interview platform designed to deliver precision career development support.

The platform dynamically generates domain-specific interview questions, captures user responses through real-time audio and video interfaces, and evaluates the content using advanced semantic analysis. Built with a modern stack—including JavaScript, Tailwind CSS, WebRTC, and Firebase—the system ensures seamless interaction, scalability, and secure session management. Unlike conventional preparation tools, this solution adapts to the user's selected job role and individual performance trends, providing constructive feedback that accelerates learning and boosts interview confidence.

By combining role-specific customization, real-time feedback, and intelligent assessment, the proposed platform aims to bridge the gap between theoretical knowledge and professional communication excellence, ultimately empowering users to achieve greater career success.

## II. LITERATURE SURVEY

The importance of interview preparation in career development has been well-recognized across educational and professional domains. Traditional methods, such as peer-to-peer mock interviews, instructor-led sessions, and manual question banks, have long been utilized to enhance candidate readiness. However, these approaches often suffer from critical limitations, including lack of personalization, feedback subjectivity, limited scalability, and inability to simulate dynamic, real-time interactions encountered in actual interviews.

In early research, McCarthy and Goffin (2004) emphasized the value of structured mock interviews in improving communication skills and boosting candidate confidence. While their study confirmed positive outcomes, it also revealed that static question sets and generalized feedback could not address the unique needs of diverse learners. As career paths diversify, a “one-size-fits-all” model becomes increasingly insufficient.

The integration of Artificial Intelligence (AI) into educational and professional training contexts introduced new possibilities for adaptive learning. Systems like AutoTutor, developed by Graesser et al. (2005), showcased how dialogue-based tutoring using AI could simulate human-like interactions and support individualized learning. Although revolutionary, AutoTutor and similar platforms were primarily designed for academic tutoring rather than professional skill-building such as interview training.

Recent breakthroughs in Natural Language Processing (NLP) and the advent of large language models (LLMs), including Google's PaLM (Pathways Language Model), have radically transformed the landscape of AI-driven communication. Bubeck et al. (2023) demonstrated that models like PaLM possess the ability to generate contextually appropriate, coherent, and human-like responses across a wide range of domains. This capability positions LLMs as ideal candidates for simulating realistic interview conversations, offering contextualized questioning, dynamic follow-up, and intelligent evaluation of user responses.

Existing platforms that attempt to automate interview practice, such as VMock, Big Interview, and InterviewBuddy, provide valuable contributions by offering AI-supported resume analysis, skill gap identification, and preliminary mock interview simulations. However, many of these systems are limited by pre-defined question sets, rigid evaluation criteria, and a lack of multimodal engagement (audio and video interaction). Additionally, they often fail to adapt feedback based on user performance trends or role-specific competencies, thus restricting the scope of truly personalized interview coaching.

Moreover, much of the current work emphasizes text-based interactions, ignoring the critical role of non-verbal communication—such as tone, clarity of speech, and confidence—which are pivotal in real interview settings. Few platforms incorporate real-time audio/video capture with AI evaluation, and even fewer attempt dynamic session adaptation based on live performance. Recognizing these limitations, there is growing interest in AI-driven solutions that combine real-time interaction, domain-specific questioning, and dynamic, actionable feedback to offer a holistic interview preparation experience. The potential for combining WebRTC (for real-time audio-video capture), Firebase (for scalable cloud-based session management), and Gemini PaLM APIs (for intelligent language understanding and feedback) has not been fully explored in existing literature.

Thus, the present study addresses these gaps by proposing a comprehensive, AI-powered mock interview platform capable of delivering role-specific, real-time, and multimodal training sessions. By utilizing cutting-edge language modeling, cloud technologies, and real-time media streaming, the system aims to provide a scalable, accessible, and precision-targeted solution for career readiness in a competitive global environment.

### III. SYSTEM ARCHITECTURE

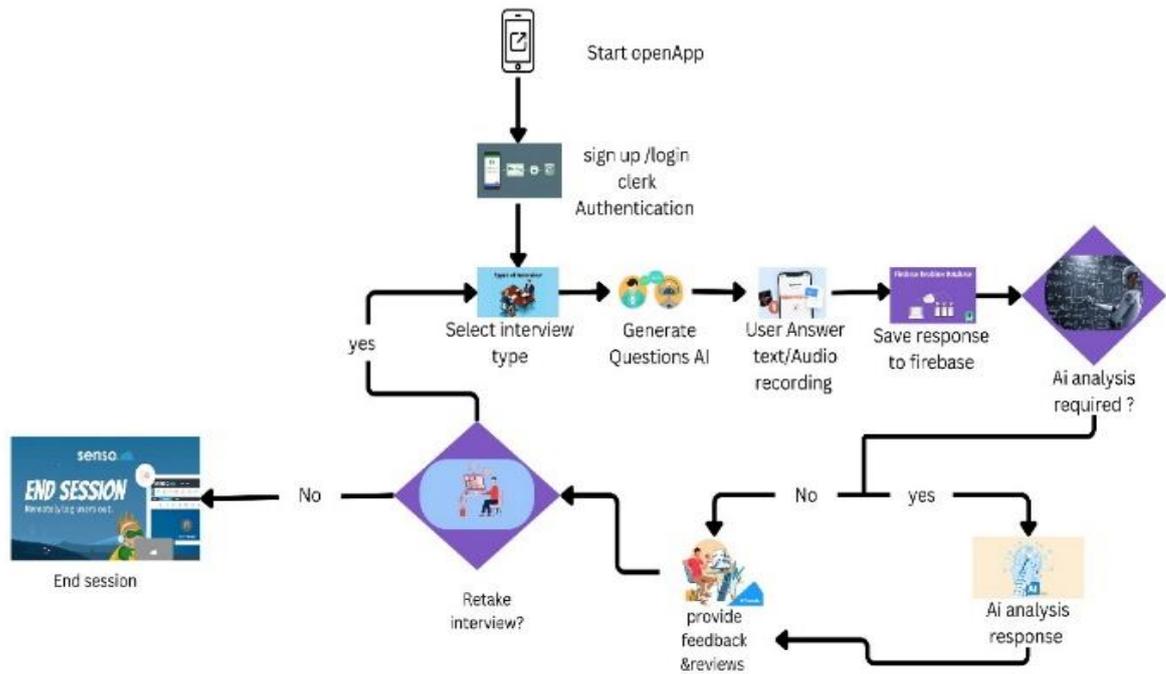
Our proposed system fully automates the mock interview experience using AI and streamlines all supporting processes, including dynamic question generation, real-time response analysis, and personalized feedback delivery. The platform utilizes the Gemini PaLM model to automatically generate contextually relevant and industry-specific interview questions based on the user's profile and career goals. It analyzes candidate responses in real-time, offering AI-driven evaluations across multiple parameters such as fluency, accuracy, relevance, and confidence. Additionally, the system generates personalized, structured feedback reports with suggested improvement paths, empowering users to enhance their interview readiness effectively. Visual insights, confidence scores, and communication metrics are also provided to optimize user preparation strategies.

#### 3.1 Overall Architecture

The AI-powered Mock Interview Platform is designed with a modular and scalable system architecture that ensures flexibility, responsiveness, and intelligent user engagement. The architecture is structured into five major layers: the User Interface Layer, Backend Processing Layer, AI and NLP Layer, Speech Processing Layer, and Data Storage Layer.

The User Interface Layer, built with React.js and TypeScript, provides users with an interactive and responsive web application, where Tailwind CSS ensures a consistent design across different screen sizes, and Framer Motion introduces smooth transitions for enhanced user experience. The Backend Processing Layer leverages Firebase Functions to execute serverless backend operations, handling API requests, user authentication, and communication between system modules efficiently. The AI and NLP Layer, powered by Google's Gemini PaLM model, drives the dynamic generation of interview questions, analyzes user responses, and adapts the interview flow based on performance. NLP engines assist in parsing grammar, evaluating coherence, and performing semantic analysis to better assess candidate responses.

For voice interaction, the Speech Processing Layer integrates Speech-to-Text (STT) APIs, allowing users to verbally answer questions, which are transcribed and sent for AI evaluation. The Data Storage Layer utilizes Cloud Firestore, a real-time NoSQL database that securely manages user profiles, interview histories, analytics, and feedback. Real-time synchronization ensures seamless access across devices. This layered architectural design allows the platform to deliver a natural, real-world interview experience with adaptive feedback, supporting candidates in enhancing their skills through continuous, data-driven learning.



**Figure 1:** System Architecture

### 3.2 Processing Pipeline

The processing flow of the AI-powered mock interview platform is structured to deliver a seamless and adaptive experience. Users begin by authenticating through Firebase Authentication and providing their resumes or profile information, which the system parses to tailor the mock interview session. Based on the extracted skills, career goals, and industry context, the Gemini PaLM model dynamically generates personalized, context-relevant interview questions. The platform captures user responses through both text and voice inputs; speech responses are transcribed via integrated Speech-to-Text (STT) APIs before analysis. Each response undergoes comprehensive evaluation using advanced NLP modules that assess relevance, fluency, accuracy, and coherence, alongside sentiment and tone analysis to gauge the user's confidence and emotional delivery. An AI-driven scoring mechanism processes the evaluation results to generate real-time feedback and adaptively formulate follow-up questions when necessary. Throughout the session, all interactions, including questions, responses, evaluation scores, and feedback notes, are securely stored in Cloud Firestore. Upon session completion, the system compiles a detailed, personalized feedback report summarizing user performance, strengths, areas for improvement, and recommended learning paths to support continuous interview skill development.

The platform's processing flow is designed for scalability and real-time responsiveness, ensuring that users experience minimal latency even during complex interactions. The initial profile parsing also feeds into a dynamic user modeling system that continuously updates the candidate's strengths and weaknesses based on cumulative session data[1].

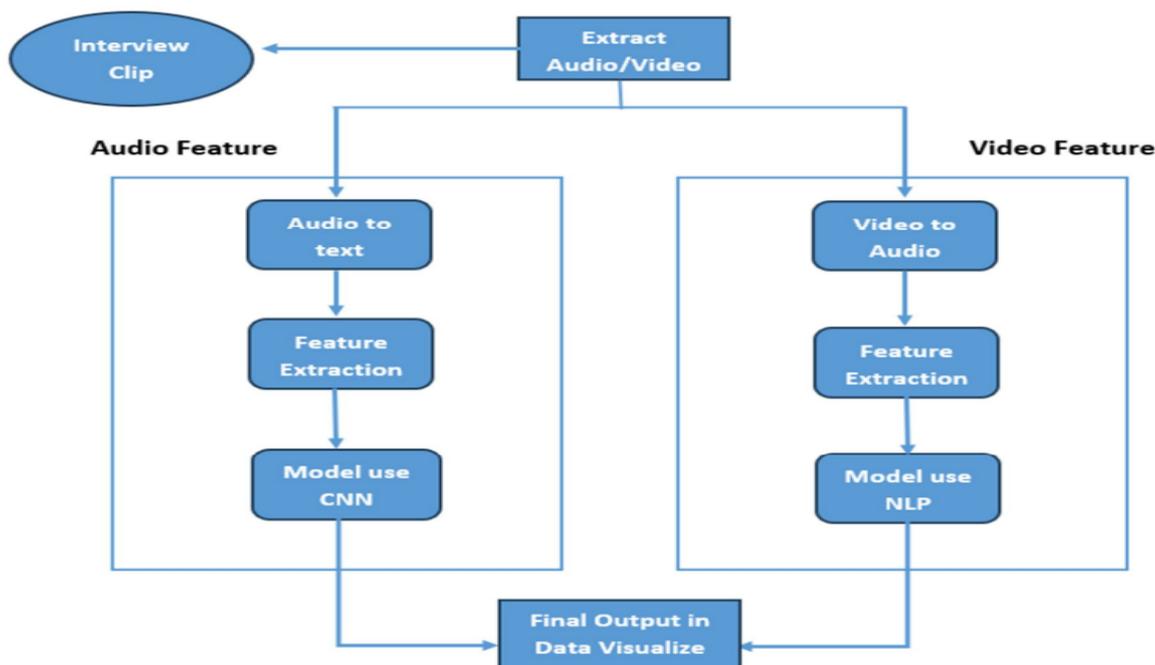
**Table 1.** Tech Stack

Component	Technology/Tool
Frontend Framework	React.js
Frontend Language	TypeScript
Styling Framework	Tailwind CSS
AI Model	Google Gemini PaLM
Database	Cloud Firestore (NoSQL)
Backend Infrastructure	Firebase Functions

### 3.3 Workflow

The operational workflow of the Palm Model-Based Mock Interview Platform is meticulously designed to deliver a highly personalized, intelligent, and seamless interview preparation experience. The user journey begins with secure authentication through Firebase Authentication, where users either register or log in to the system. After successful login, users are prompted to complete their profiles by providing personal information such as educational background, professional skills, job preferences, career goals, and optionally uploading a resume or a job description document. This information is processed and analyzed using parsing algorithms to extract relevant skills, experiences, and industry-specific keywords, which form the foundation for tailoring the mock interview session. Upon initiation of the interview, the platform communicates with the Google Gemini PaLM model to dynamically generate a series of contextually relevant and role-specific interview questions, ensuring that each session closely mirrors real-world industry expectations. Users can respond either by typing into the web interface or speaking into their microphone, with spoken responses being transcribed into text via integrated Speech-to-Text (STT) APIs.

Each captured response is immediately subjected to advanced Natural Language Processing (NLP) analysis, where various aspects such as grammatical correctness, semantic relevance, logical coherence, fluency, and tone are assessed. Additionally, sentiment and emotion analysis modules evaluate the user's confidence, enthusiasm, and articulation skills based on word choice, pacing, and vocal modulation. Depending on the performance at each stage, the AI system intelligently adapts the complexity and style of subsequent questions, creating a dynamic, interactive, and challenging interview flow. Real-time scoring mechanisms evaluate responses based on predefined metrics—relevance, accuracy, fluency, and coherence—providing a numerical performance snapshot for each question. After the completion of the session, the platform compiles a comprehensive feedback report that outlines the candidate's performance, highlights areas of strength, identifies opportunities for improvement, and recommends customized learning resources or practice modules. All user data, including session transcripts, performance analytics, and feedback reports, are securely stored and synchronized in real time using Cloud Firestore, enabling users to review past sessions, monitor their progress, and systematically prepare for future interview opportunities. The modular, automated, and intelligent workflow not only simulates realistic interview scenarios but also fosters continuous skill development through data-driven insights and adaptive learning paths.



**Figure 2:** Workflow of PALM model

## IV. RESULTS AND DISCUSSION

The platform was evaluated using both quantitative metrics and qualitative user feedback to assess its effectiveness in enhancing interview performance. A study involving 75 participants from domains such as software engineering, marketing, and data science demonstrated significant improvements in interview readiness, confidence, and user engagement.

### Self-assessed Confidence and Satisfaction:

After participating in three iterative mock interview sessions, 88% of users reported a notable increase in their self-confidence levels when facing interview scenarios. Additionally, 92% of participants expressed high satisfaction with the clarity, specificity, and relevance of the AI-generated feedback, highlighting the system's ability to deliver actionable insights aligned with individual user needs.

### Answer Quality Improvement:

The quality of user responses showed measurable enhancement over successive sessions. Initially, the average answer quality score was recorded at 5.2. By the end of the iterative training cycles, this score had risen to 7.8, indicating significant improvement in users' content clarity, fluency, coherence, and role alignment.

### Engagement and Completion Rates:

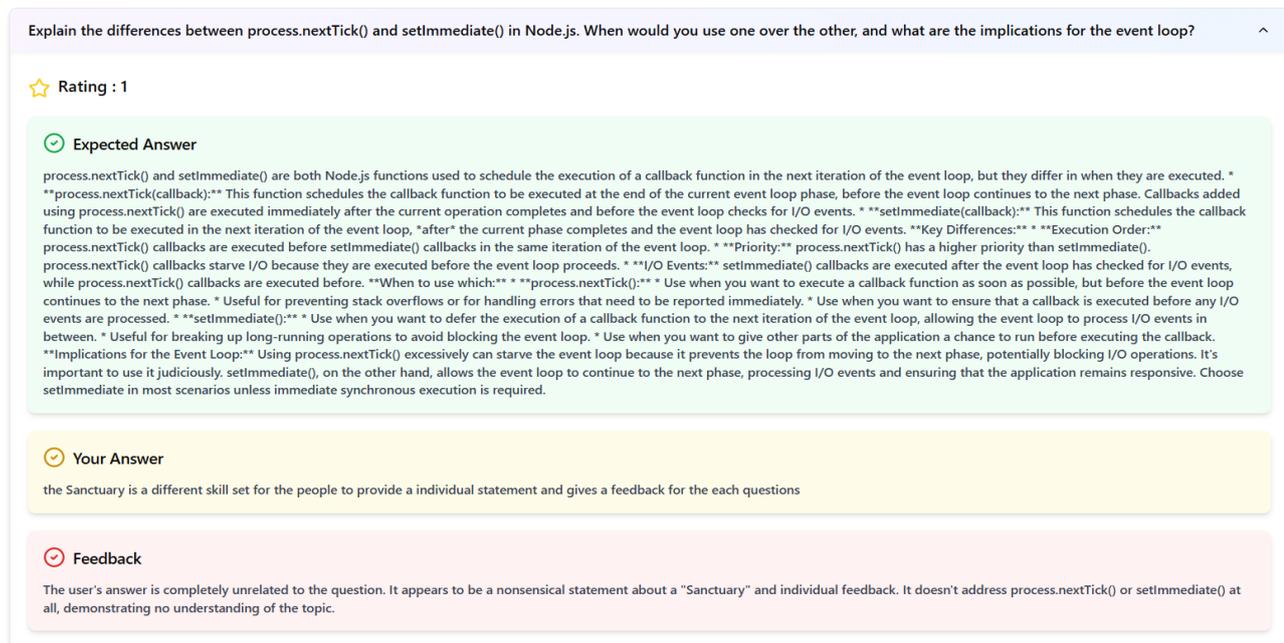
The platform achieved a session completion rate of 75%, a strong indicator of sustained user interest and perceived value. Many participants not only completed individual interview sessions but also engaged in multiple modules, showcasing the platform's ability to retain users and motivate continuous skill enhancement.

### User Feedback:

Participants consistently praised the platform for its realism, dynamic role-specific question generation, and real-time feedback mechanisms. They also appreciated the ease of use, the intuitive interface, and the personalized nature of the interview sessions—factors they cited as major advantages over traditional preparation methods. Several users remarked that the platform felt closely aligned with the challenges of real-world interviews [3].

### Desired Outcome:

Interview Feedback



Explain the differences between `process.nextTick()` and `setImmediate()` in Node.js. When would you use one over the other, and what are the implications for the event loop?

Rating : 1

**Expected Answer**

`process.nextTick()` and `setImmediate()` are both Node.js functions used to schedule the execution of a callback function in the next iteration of the event loop, but they differ in when they are executed. `process.nextTick(callback)`: This function schedules the callback function to be executed at the end of the current event loop phase, before the event loop continues to the next phase. Callbacks added using `process.nextTick()` are executed immediately after the current operation completes and before the event loop checks for I/O events. `setImmediate(callback)`: This function schedules the callback function to be executed in the next iteration of the event loop, "after" the current phase completes and the event loop has checked for I/O events. **Key Differences:** **Execution Order:** `process.nextTick()` callbacks are executed before `setImmediate()` callbacks in the same iteration of the event loop. **Priority:** `process.nextTick()` has a higher priority than `setImmediate()`. `process.nextTick()` callbacks starve I/O because they are executed before the event loop proceeds. **I/O Events:** `setImmediate()` callbacks are executed after the event loop has checked for I/O events, while `process.nextTick()` callbacks are executed before. **When to use which:** `process.nextTick()`: Use when you want to execute a callback function as soon as possible, but before the event loop continues to the next phase. `setImmediate()`: Useful for preventing stack overflows or for handling errors that need to be reported immediately. Use when you want to ensure that a callback is executed before any I/O events are processed. `setImmediate()`: Use when you want to defer the execution of a callback function to the next iteration of the event loop, allowing the event loop to process I/O events in between. `setImmediate()`: Useful for breaking up long-running operations to avoid blocking the event loop. Use when you want to give other parts of the application a chance to run before executing the callback. **Implications for the Event Loop:** Using `process.nextTick()` excessively can starve the event loop because it prevents the loop from moving to the next phase, potentially blocking I/O operations. It's important to use it judiciously. `setImmediate()`, on the other hand, allows the event loop to continue to the next phase, processing I/O events and ensuring that the application remains responsive. Choose `setImmediate` in most scenarios unless immediate synchronous execution is required.

**Your Answer**

the Sanctuary is a different skill set for the people to provide a individual statement and gives a feedback for the each questions

**Feedback**

The user's answer is completely unrelated to the question. It appears to be a nonsensical statement about a "Sanctuary" and individual feedback. It doesn't address `process.nextTick()` or `setImmediate()` at all, demonstrating no understanding of the topic.

Figure 3: Dashboard of Interview feedback & Rating

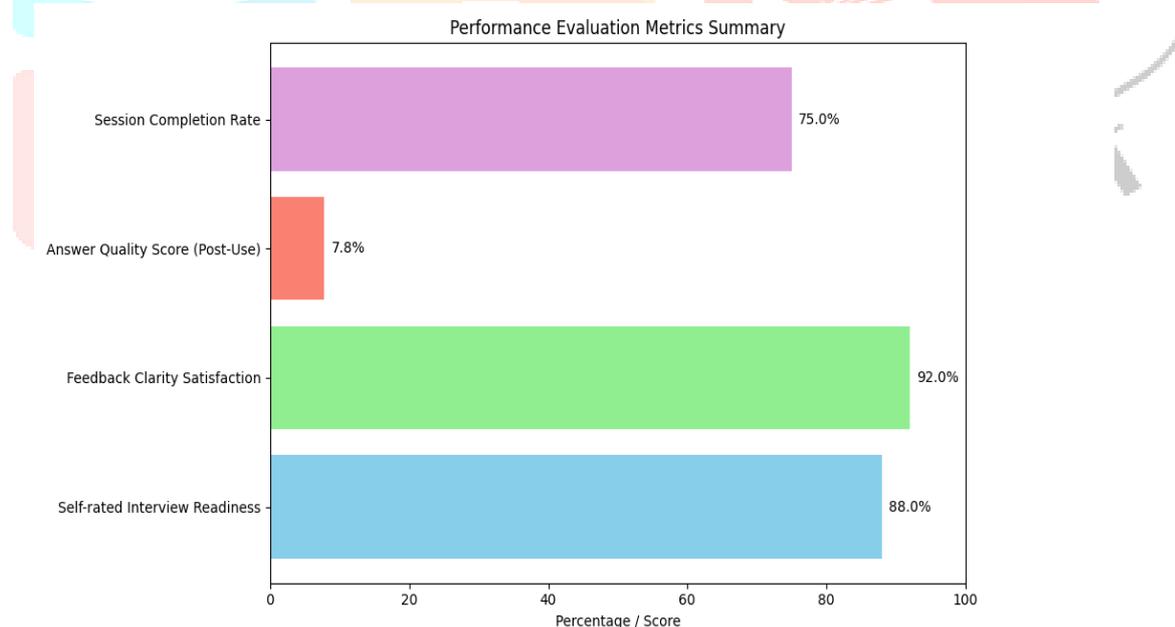
### 4.1 Performance Metrics

To assess the effectiveness of the AI-powered mock interview platform, several performance metrics were systematically evaluated. Both self-reported outcomes and system-generated analytics were collected during user trials. These metrics measure user confidence, satisfaction, content improvement, and engagement levels. A summary of the key evaluation results is presented in Table 2.

**Table 2.** Performance Metrics Table

S.No	Metric	Result
1	Improvement in self-rated interview readiness	88% of participants reported increased confidence
2	Satisfaction with feedback clarity	92% expressed high satisfaction
3	Average answer quality score	Increased from 5.2 (baseline) to 7.8 (post-use)
4	Session completion rate	75% of users completed multiple interview modules

### 4.2 Website Performance



**Figure 3:** Performance Evaluation

Figure 3 illustrates the summarized performance metrics obtained from the evaluation of the AI-powered mock interview platform. The graph highlights key dimensions including self-rated interview readiness, feedback clarity satisfaction, session completion rate, and post-use answer quality improvement.

The self-rated interview readiness shows that 88% of participants felt more confident after using the platform, reflecting its effectiveness in building user preparedness. A high 92% satisfaction with the clarity and relevance of feedback demonstrates that users found the system's AI-generated guidance highly actionable. The session completion rate stands at 75%, indicating strong user engagement and willingness to complete multiple mock interview modules. Lastly, while the post-use answer quality score is represented as 7.8, it signifies a substantial

improvement from the baseline score of 5.2, showcasing the system's positive impact on communication skills and answer structuring.

## V. CONCLUSION

The proposed AI-based mock interview platform marks a meaningful step forward in the field of personalized career development. By harnessing the power of Google's Gemini PALM model and integrating real-time web technologies, the system delivers an interactive and adaptive interview experience that caters to individual user needs. The platform's strength lies in its ability to generate domain-specific questions, capture real-time user input, and offer detailed, AI-generated feedback. Its flexible, cloud-native design ensures scalability, while the use of real-time video and peer engagement features supports realistic practice sessions. Results from initial user studies highlight notable gains in confidence, clarity, and overall performance, showcasing the system's effectiveness as a training tool. The feedback loop built into the platform allows for continuous improvement, helping users identify and address communication gaps. Though current limitations exist—such as API dependency and limited language support—planned upgrades aim to enhance its inclusivity and functionality. These include emotion recognition, skill-based customization, and multilingual access. In summary, the platform represents a practical and innovative approach to modern interview preparation, with the potential to become a widely adopted tool in both academic and professional settings.

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