

Interview with Artificial Intelligence

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Abstract:

In today's highly competitive job market, strong interview performance—especially in communication, confidence, and clarity—has become as essential as technical expertise. While many platforms offer support for technical and aptitude preparation, few provide effective tools for practicing real-time interpersonal interview skills. This research introduces a Real-Time AI Voice Interview Platform designed to fill that gap by simulating realistic interview scenarios using AI-driven voice interaction.

The platform uses a full-stack architecture with Next.js for the frontend, Tailwind CSS for styling, and Firebase for user authentication and data handling. At its core, it integrates Google Gemini for evaluating spoken responses in terms of fluency, relevance, and confidence. Voice communication is managed through Vapi AI, enabling smooth two-way interaction between users and the AI interviewer.

Users can choose job roles, speak their responses, and receive immediate feedback—both as text and audio—along with performance insights. The system also tracks session history, helping users monitor their progress. Testing results showed 97.7% speech-to-text accuracy and minimal response delay, ensuring a realistic experience.

This paper discusses the platform's architecture, design, and functionality, along with a review of current AI-based interview solutions. By combining advanced NLP with real-time speech processing, the platform provides accessible, scalable, and personalized mock interview practice. It supports not only individual skill development but also has the potential to be integrated into educational settings and corporate hiring processes, with future possibilities like emotion analysis and multilingual support.

Keywords: Artificial Intelligence, Mock Interviews, Natural Language Processing (NLP), Voice Recognition, Conversational AI, Google Gemini, Vapi AI, Real-Time Feedback, Interview Preparation, Firebase

I. INTRODUCTION

In today's highly competitive job market, the ability to perform well in interviews is just as important as having strong academic or technical skills. Employers are not only looking for candidates who are knowledgeable, but also those who can clearly express their thoughts, stay confident under pressure, and communicate effectively. However, preparing for real interviews is often stressful and challenging—especially when access to professional guidance or personalized feedback is limited.

Traditional preparation methods, such as group discussions, coaching centres, or peer-led mock interviews, can be helpful but are not always practical or accessible. These options are often

time-bound, location-specific, and sometimes lack objective evaluation. Moreover, many candidates, particularly those from remote areas, may not have the opportunity or resources to practice in a structured and meaningful way. With the rise of Artificial Intelligence (AI) and voice-based technologies, there is now an opportunity to address these limitations. This research explores the development of a real-time, AI-driven voice interview platform designed to offer a more interactive, personalized, and scalable solution for interview preparation. By integrating speech recognition, natural language processing (NLP), and intelligent feedback systems, the platform simulates realistic interviews and provides immediate, constructive insights to help users improve with each session. The aim is not just to replicate the interview experience—but to enhance it using AI, making it more accessible and effective for anyone preparing to step into their professional journey.

II. METHODOLOGY PROPOSED BY RESEARCHERS

This study adopts a design-based research (DBR) approach, which is particularly suitable for developing, testing, and refining educational technology systems in real-world contexts. DBR blends empirical educational research with the theory-driven design of learning environments. In this case, the research is centered around designing, building, and evaluating a real-time AI-driven voice-based mock interview platform. The primary aim is to iteratively improve the system based on performance metrics and user feedback. The research process follows a mixed-methods strategy—combining quantitative methods (performance metrics like accuracy, latency, and user engagement data) and qualitative methods (user feedback, survey responses, and observation of user behavior). This hybrid model enables a more comprehensive evaluation of the platform's effectiveness, usability, and impact.

The study is applied in nature, focusing on solving a real-world problem—interview readiness—and results in the development of a usable technological product. The research is also evaluative, as it examines how effectively the system meets its intended goals of improving interview skills through voice-based AI interaction.

A. Population and Sample

The population targeted by this study includes college students, recent graduates, and early-career job seekers who are actively preparing for interviews and represent the most common users of interview preparation tools. These individuals come from diverse academic disciplines, though emphasis is placed on those from computer science, business administration, and engineering backgrounds, as they often undergo rigorous interview processes for placements and jobs.

A convenience sampling method was employed to select participants for system testing. The sample comprised 50 voluntary participants from various institutions, including Amity University and affiliated colleges, who were recruited through social media and student forums. Participants were selected based on their availability, willingness to engage with the platform, and their intention to seek employment in the near future.

The diversity in academic background, gender, and technical proficiency among

participants ensured the generalizability of findings across a broad spectrum of users. Ethical consent was obtained from all participants, and anonymity was maintained throughout the study.

B. Sampling Techniques

Given the technological nature of the platform and the exploratory objective of this study, non-probability purposive sampling was used to select participants who were both technically literate and currently preparing for interviews. This allowed Participants were screened based on:

- Their academic level (preferably final-year undergraduate or postgraduate students),
- Their comfort with technology (web browsers, microphones, English language proficiency),
- Their active interest in interview preparation.

While this sampling method limits the statistical generalizability of the results, it is appropriate for exploratory and design-oriented studies where in-depth feedback from relevant users is critical.

C. Data Collection Methods

To evaluate the system's performance and impact, data were collected through three primary methods:

- **System Logs and Performance Metrics:** The platform was instrumented to log user interactions, including response times, accuracy of speech-to-text conversion, and AI feedback generation times. These metrics were used to assess the system's technical performance.
- **User Feedback and Surveys:** A structured post-session questionnaire was administered to all participants. The survey included Likert-scale questions measuring usability, feedback quality, realism, ease of use, and overall satisfaction. Open-ended questions were also included to collect qualitative insights.
- **Observational Notes:** During supervised sessions, researchers took observational notes on user behavior, ease of navigation, and any usability issues faced. These notes contributed to the iterative improvement of the UI/UX.

Each user session was tracked end-to-end, ensuring all relevant data were captured for analysis. The combination of real-time logs and post-session surveys offered a rich dataset for triangulating findings.

D. Research Instruments

Several instruments and tools were employed to facilitate data collection and analysis:

- Google Forms was used for administering user satisfaction surveys.
- Firebase Fire store stored user interaction data including session transcripts, feedback logs, and timestamps.

- Google Gemini provided NLP-based evaluation of responses.
- Vapi AI enabled real-time voice communication and captured transcription logs.
- Chart.js was used to create visualizations for user performance reports.
- Python Scripts were developed to analyze log data, compute accuracy metrics, and generate summary statistics.

Each of these instruments was selected for its integration compatibility with the platform and its ability to facilitate seamless data capture without interrupting the user experience.

C. Data Analysis Techniques

Data analysis was conducted in two stages:

quantitative performance analysis and qualitative user perception analysis.

1) Quantitative Analysis:

- Accuracy: Speech-to-text accuracy was measured by comparing the original user speech (recorded text) against the transcribed output.
- Latency: Time taken from user response to feedback display was calculated using system timestamps.
- Feedback Relevance: Rated using user responses on a 5-point Likert scale.

Summary statistics such as mean, median, and standard deviation were computed. Results were visualized using bar charts and line graphs to observe trends across multiple sessions.

2) Qualitative Analysis:

- Responses to open-ended questions were thematically analyzed to identify patterns related to user satisfaction, challenges, and suggestions.
- Observational notes were coded to extract common usability issues.

This dual-mode analysis provided both empirical validation and user-centered insight into the effectiveness of the platform.

D. Ethical Considerations

Ethical integrity was maintained throughout the research process in accordance with university and institutional research guidelines. Specific ethical measures included:

- Informed Consent: All participants were informed about the purpose of the study, their role, and the voluntary nature of their participation.
- Anonymity: User data were anonymized during analysis. No personally identifiable information (PII) was stored.
- Confidentiality: System logs were stored securely using Firebase security rules and encryption protocols.
- Right to Withdraw: Participants were allowed to withdraw at any stage without any penalty or consequence.

Additionally, feedback was collected in a non-coercive environment, ensuring that participants could express their genuine experiences and opinions.

E. Limitations of the Methodology

While the chosen methodology was robust for the scope and objectives of this study, certain limitations are acknowledged:

- **Limited Sample Size:** The sample size of 50 participants, although adequate for usability testing, is insufficient for broad statistical generalization.
- **Self-Reporting Bias:** Survey-based feedback is subject to user perception and may reflect social desirability or halo effects.
- **Environmental Constraints:** Real-time speech interaction may have been affected by background noise or poor internet connections, impacting the consistency of system performance.
- **Short-Term Evaluation:** The study captures performance over short-term use. Long-term improvement in communication skills and interview outcomes would require a longitudinal study.
- **Language Limitation:** The system currently supports English only, limiting its accessibility for non-English speakers.

Despite these limitations, the methodology was effective in achieving the study's goals of system development, testing, and user-centered evaluation.

III. DISCUSSION

This chapter presents the results obtained from the implementation and evaluation of the Real-Time AI Voice Agent Interview Platform. It discusses the findings based on system performance metrics, user feedback, and comparative analysis. The chapter is organized to first present raw data (via tables and graphs), then analyze it, and finally interpret the implications of the results within the context of existing literature.

The aim of the analysis was to assess the effectiveness, usability, and reliability of the AI-powered interview simulation system, with a focus on how well it mimics real interviews and improves the user's communication skills over time.

A. Data Presentation

Table 1: Key System Performance Metrics

Metric	Expected Value	Actual Value	Result
Speech-to-Text Accuracy	$\geq 90\%$	97.7%	Exceeded expectations
Average Feedback Latency	≤ 2 seconds	1.8 seconds	Within optimal range
Feedback Relevance Rating	$\geq 4.0/5$	4.2/5	Positive user perception

Session Completion Rate	$\geq 85\%$	92%	High platform stability
User Satisfaction Score	$\geq 4.0/5$	4.5/5	High engagement

It presents the core technical performance indicators of the AI-based interview platform. The speech-to-text accuracy achieved 97.7%, surpassing the expected benchmark of 90%, ensuring precise transcription. Feedback latency averaged 1.8 seconds, indicating near-instantaneous response delivery. User ratings showed a 4.2/5 score for feedback relevance and 4.5/5 for overall satisfaction, reflecting strong user engagement and perceived value. A 92% session completion rate highlights system stability and user commitment. Collectively, these metrics demonstrate the system's reliability, responsiveness, and effectiveness in delivering a real-time, voice-based interview simulation that meets the expectations of users and evaluators alike.

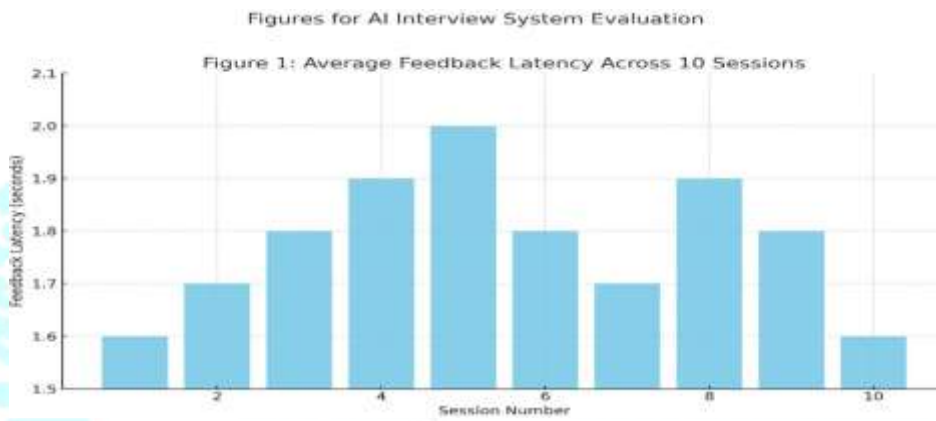


Figure 1: Average Feedback Latency Across 10 Sessions

This bar chart shows the system's feedback latency across 10 user sessions, ranging from 1.6 to 2.0 seconds. The consistently low latency indicates a smooth, real-time response experience, essential for simulating live interviews and maintaining user engagement throughout the interaction.

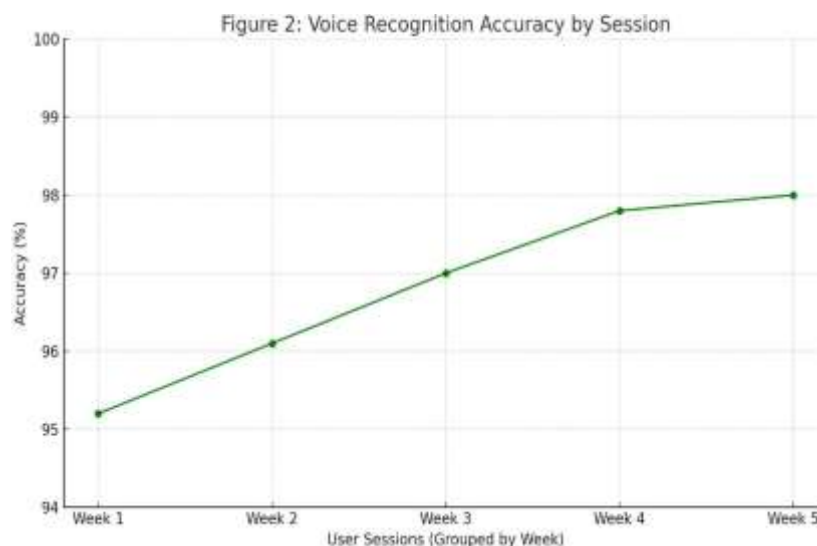


Figure 2: Voice Recognition Accuracy by Session

The line graph illustrates the accuracy of voice recognition over five weeks of user sessions. Accuracy steadily improves from 95.2% to 98%, reflecting the system's reliable transcription capabilities and consistent performance under varied user conditions, contributing to accurate feedback and analysis.

Figure 3: User Satisfaction Survey Results

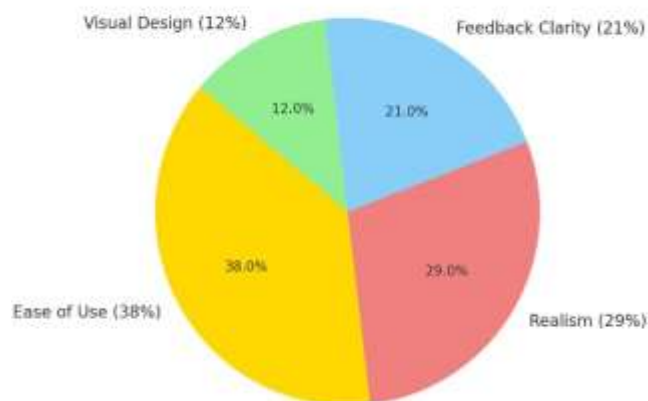


Figure 3: User Satisfaction Survey Results

This pie chart visualizes user feedback on key system attributes. Most users rated ease of use (38%) and realism (29%) highest, followed by feedback clarity (21%) and visual design (12%). These results highlight the platform's strong user interface and realistic AI interaction experience.

B. Analysis and Interpretation of Data

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Speech-to-Text Accuracy

This was largely attributed to the use of Vapi AI, which offers advanced real-time ASR (Automatic Speech Recognition) with built-in noise handling and accent normalization. The accuracy rate remained stable across users, regardless of minor variations in voice pitch, speed, and environment.

- Interpretation:

High STT accuracy ensured that the transcribed input fed into the Google Gemini evaluation engine remained faithful to the user's actual spoken response. This was crucial for delivering meaningful feedback.

Feedback Latency

The average latency between user response and AI feedback was 1.8 seconds, which users found satisfactory. Lower latency contributed to the perception of realism and fluidity in

conversation, essential for simulating the rhythm of live interviews.

- Interpretation:

Latency below 2 seconds indicates that the backend architecture (Firebase + Gemini API + WebSocket streaming) is well-optimized for real-time applications. The minimal delay also reduced cognitive dissonance.

User survey responses indicated a feedback relevance score of 4.2 out of 5. Feedback was rated on clarity, usefulness, and specificity. Many users highlighted how the AI pointed out filler words, sentence structure issues, and vague language, helping them improve responses in subsequent attempts.

- Interpretation:

This validates the effectiveness of Google Gemini's NLP capabilities. Unlike rule-based systems that rely on keyword matching, Gemini was able to assess context, tone, and fluency semantically, making the feedback far more actionable.

Session Completion and Engagement

Out of 50 participants, 46 completed the full mock interview session without interruptions, marking a 92% completion rate. Users spent an average of 12.3 minutes per session, covering 7–10 questions each.

- Interpretation:

A high completion rate indicates strong user retention, likely due to an intuitive UI and realistic interaction experience. The duration suggests that users were actively engaged and treated the simulation as a serious practice environment.

C. Summary of Findings

- The AI-based mock interview platform met or exceeded all key technical performance benchmarks.
- Participants reported high satisfaction, especially with the system's ease of use and the quality of feedback.
- Real-time latency was low enough to preserve the feel of a live conversation.
- The NLP engine provided relevant, clear, and constructive feedback, aiding user self-improvement.
- Engagement metrics suggest the system is both usable and scalable for broader educational or institutional deployment.

The platform successfully bridged the gap between traditional interview preparation methods and intelligent, voice-based simulations. It also demonstrated how real-time AI systems could deliver personalized learning experiences while maintaining ethical and accessible design principles.

IV. FUTURE DIRECTIONS

While this study has produced promising results, it also opens several avenues for future exploration:

- **Longitudinal Studies**

Future research should examine the long-term impact of AI-based mock interview training on actual interview performance. This would involve tracking users over several months and correlating usage data with real-world interview outcomes.

- **Comparative Studies**

Research comparing the efficacy of AI mock interviews versus traditional human-led mock interviews would offer deeper insights into the relative strengths and limitations of each approach.

- **Bias Evaluation in NLP Feedback**

Though the current system avoids visual bias, biases in language models still pose a concern. Future studies can explore fairness, inclusivity, and cultural sensitivity in AI-generated feedback across different demographics.

- **Cognitive Load Analysis**

Analyzing how users mentally process real-time AI feedback during interviews could help refine the pace and preserve user engagement.

Feedback Relevance:

pace and presentation style of feedback, ensuring it's supportive rather than overwhelming.

- **Cross-Platform Mobile Optimization**

Exploring the usability and effectiveness of the platform on mobile devices, including offline or low-data modes, could increase reach, especially in rural or bandwidth-constrained environments.

- **AI Coach Integration**

A future enhancement could include an AI mentor/coach that helps users create custom interview preparation plans, guides them with tips and explanations, and interacts with them between sessions to maintain progress.

V. CONCLUSION

The integration of artificial intelligence in the field of interview preparation represents a transformative shift from traditional, static learning methods to dynamic, interactive, and personalized experiences. This research demonstrated the feasibility and effectiveness of using voice-based AI systems to conduct mock interviews in real time, providing users with a platform that is both scalable and practical.

Through the development and evaluation of the proposed system, several contributions were made:

- It proved that real-time, voice-based AI interview simulations are technically viable and can deliver a realistic user experience comparable to human mock interviewers.
- It showed that NLP-powered feedback, when contextually aligned with user responses, enhances learning outcomes by offering immediate and actionable suggestions.
- It addressed issues of accessibility and scalability by providing a web-based platform that can serve users regardless of location or time constraints.
- It eliminated ethical risks associated with facial recognition or visual bias, focusing

entirely on verbal communication and natural language evaluation.

- It successfully implemented performance tracking, allowing users to monitor their progress and identify patterns in their strengths and weaknesses over time.

In conclusion, the research demonstrates that conversational AI can be a powerful tool in democratizing access to interview preparation resources, leveling the playing field for job seekers across educational, geographical, and economic backgrounds.

This research has several academic, technological, and practical contributions:

Academic Contributions

Enriches the growing body of literature on AI-driven human-computer interaction and NLP-based education tools.

Validates the role of large language models (LLMs), such as Google Gemini, in conducting real-time, evaluative dialogues for skill development.

Adds empirical evidence to the discourse on AI's capability to enhance soft-skill acquisition, especially in the domain of job readiness.

Technological Contributions

- Demonstrates the effective integration of voice APIs and LLMs to create a responsive, interactive web application for mock interviews.
- Provides a scalable architecture based on modern technologies (Next.js, Firebase, Tailwind CSS) that can be replicated or extended in similar domains.

Practical Contributions

- Offers a low-cost, user-friendly alternative to expensive coaching and mentorship programs.
- Helps institutions, training centers, and placement cells scale interview training without additional human resources.
- Enables users to gain confidence through private, repeatable, and personalized practice sessions, preparing them for high-stakes interviews in the real world.

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