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A Context-Aware Generative AI Framework for Automated Interview Evaluation and Intelligent Feedback Generation

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Abstract:

The rapid adoption of Artificial Intelligence (AI) in recruitment has created new opportunities for improving the efficiency, consistency, and scalability of interview evaluation. Traditional interview processes often rely on subjective human judgment, delayed feedback, and inconsistent assessment criteria, which can negatively affect hiring quality and candidate experience [1], [2]. Recent studies have shown that AI-assisted interview systems can improve evaluation accuracy by analyzing candidate responses, communication patterns, and behavioral cues in virtual interview settings [1], [4], [9]. In parallel, advancements in Large Language Models (LLMs) have demonstrated strong capability in contextual understanding, semantic reasoning, and automated feedback generation, making them highly suitable for intelligent interview assessment applications [1], [8], [14]. This paper presents an AI-powered automated interview feedback generation system that integrates Speech-to-Text (STT), Natural Language Processing (NLP), and Large Language Models (LLMs) to provide real-time and structured candidate evaluation. The proposed system begins with role-specific interview initialization through a lightweight web-based interface, where candidate details and job preferences are collected. Based on the selected role, the system dynamically generates technical and behavioral interview questions tailored to the candidate profile [3], [8]. During the interview session, candidate responses are captured through audio input and converted into text using speech recognition. The transcribed responses are analyzed using NLP techniques to evaluate communication clarity, response relevance, logical flow, and answer quality [9], [11], [12]. An LLM-based semantic evaluation module further assesses contextual understanding, identifies strengths and weaknesses, and generates personalized feedback. The system then produces a detailed audit report comprising competency-wise scores, overall performance summaries, skill gap analysis, and actionable recommendations. The proposed framework offers a lightweight, scalable, and practical end-to-end solution for intelligent interview assessment, reducing evaluator bias, improving feedback consistency, and enabling efficient decision-making in modern digital recruitment workflows [5], [6], [15].

Keywords — Artificial Intelligence, Speech-to-Text, Natural Language Processing, Large Language Models, Automated Interview Assessment, Candidate Evaluation, Real-Time Feedback, Semantic Analysis, Recruitment Analytics, Web-Based Interview System.

1. Introduction

The rapid digital transformation of recruitment processes has significantly changed how organizations identify, assess, and hire talent. Job interviews remain one of the most widely used selection methods because they allow employers to evaluate a candidate's technical competence, communication ability, confidence, and role suitability. However, traditional interview processes often depend on subjective human judgment, which can lead to inconsistent evaluation, unconscious bias, delayed feedback, and scalability challenges, especially when handling a large number of applicants [1], [2], [25].

The COVID-19 pandemic accelerated the adoption of online and asynchronous interview systems, making virtual interviews a standard practice in modern hiring workflows [1], [10]. In asynchronous video interviews and remote screening systems, candidates respond to questions through digital platforms, enabling organizations to conduct interviews efficiently across locations. Recent research has shown that AI-assisted interview systems can improve the efficiency and objectivity of candidate assessment by analyzing speech, facial cues, response quality, and behavioral patterns [1], [9], [11].

Several existing systems have focused on specific interview-related tasks. AI-based interviewer coaching platforms provide post-session feedback to improve interviewer behavior [2], while skill-oriented question recommendation systems support adaptive question generation [3]. Mock interview systems using CNNs, multimodal analysis, and avatar-based coaching have shown positive outcomes in reducing candidate anxiety and improving communication skills [4], [8], [9], [10]. However, many such systems either require expensive infrastructure, support only simulation use cases, or lack an integrated end-to-end framework for real-time candidate evaluation and personalized feedback.

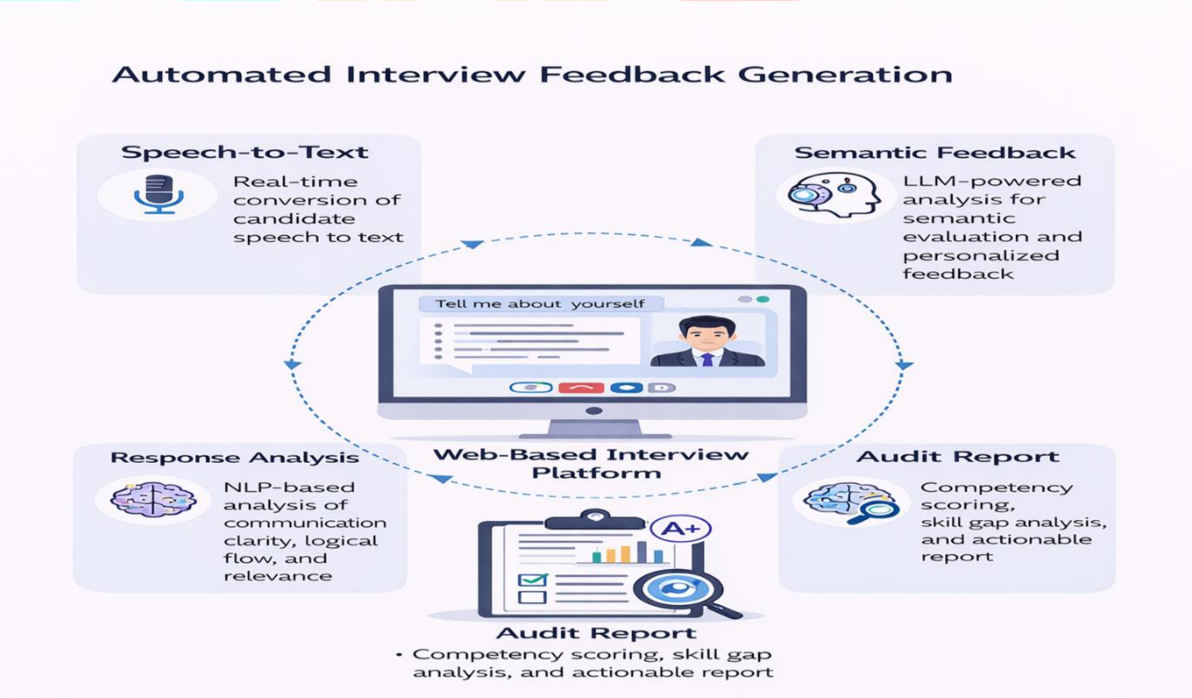

Fig. 1: Automated Interview Feedback Generation

Recent advances in Large Language Models (LLMs) have introduced powerful capabilities in contextual understanding, semantic reasoning, and automated feedback generation [1], [8], [14], [15]. These models can interpret candidate responses more effectively than rule-based systems and can provide nuanced feedback without requiring extensive task-specific retraining. This makes LLMs highly suitable for intelligent recruitment applications.

Motivated by these challenges and opportunities, this work proposes an AI-powered automated interview feedback generation system that combines Speech-to-Text (STT), Natural Language Processing (NLP), and LLM-based semantic evaluation to provide structured, real-time interview assessment. The proposed system is designed as a lightweight web-based platform that supports dynamic interview sessions, response analysis, competency-wise scoring, and actionable audit reports. The main contributions of this work are as follows:

- A web-based AI interview platform for role-specific interview simulation.
- Real-time speech-to-text conversion for candidate response capture.
- NLP-based analysis for communication clarity, logical flow, and relevance assessment.
- LLM-powered semantic evaluation and personalized feedback generation.

The proposed system aims to improve evaluation consistency, reduce recruiter workload, and provide meaningful developmental feedback to candidates, thereby offering an efficient and scalable solution for modern digital hiring workflows.

2. Literature Review

Year	Author(s)	Title	Methodology	Algorithms / Techniques	Limitations	Gap Identified
2025	Taufiq Daryanto, Xiaohan Ding, Lance T. Wilhelm, Sophia Stil, Kirk McInnis Knutsen, Eugenia H. Rho	Conversate: Supporting Reflective Learning in Interview Practice Through Interactive Simulation and Dialogic Feedback	Developed a web-based interview simulation platform with reflective learning and dialogic feedback	LLM-based interview simulation, transcript annotation, conversational feedback	Limited sample size; focused on interview practice only	No end-to-end automated scoring for real interview assessment
2024	G. C. Dixon, R. M. P. M. Ariyarathne, S. Srithanujan, K. L. Weerasinghe, H. D. T. N. Ranaweera, N. Gamage	ML-Driven HR System: Candidate Assessment for Enhanced Recruitment Outcomes	Proposed an ML-driven online recruitment and candidate verification framework	SVM, CNN, LLMs, sentiment analysis, ensemble learning	High system complexity; infrastructure intensive	Lacks lightweight and scalable interview feedback framework
2024	Tianyi Zhang, Antonis Koutsoumpis, Janneke K. Oostrom, Djurre Holtrop, Sina Ghassemi, Reinout E. de Vries	Can Large Language Models Assess Personality From Asynchronous Video Interviews? A Comprehensive Evaluation of Validity, Reliability, Fairness, and Rating Patterns	Compared GPT-3.5 and GPT-4 with human raters using AVI responses of 685 participants	GPT-3.5, GPT-4, zero-shot evaluation, psychometric analysis	Fairness concerns; reliability limitations	Lacks integrated real-time interaction and actionable feedback
2024	Sarinasadat Hosseini, Jingyu Quan, Xiaoqi Deng, Yoshihiro Miyake, Takayuki Nozawa	Avatar-Based Feedback in Job Interview Training Impacts Action Identities and Anxiety	Conducted avatar-based mock interview training experiments	Avatar simulation, behavioral analysis, anxiety assessment	Small sample size; training-focused	No automated semantic response evaluation
2024	Anna Luca Heimann, Annika	Observing Interviewees' Inner Self: How Authenticity Cues	Behavioral observation study using	Authenticity cue analysis, verbal and nonverbal	Requires manual expert observation	No AI-driven real-time authenticity assessment

Year	Author(s)	Title	Methodology	Algorithms / Techniques	Limitations	Gap Identified
	Schmitz-Wilhelmy	in Job Interviews Relate to Interview and Job Performance	mock interview videos	behavior modeling		
2024	Xinyi Luo, Yuyang Wang, Lik-Hang Lee, Zihan Xing, Shan Jin, Boya Dong, Yuanyi Hu, Zeming Chen, Jing Yan, Pan Hui	Using a Virtual Reality Interview Simulator to Explore Factors Influencing People's Behavior	Developed VR-based interview simulator with orthogonal experiments	VR simulation, EDA analysis, NASA-TLX	Expensive setup; limited accessibility	No scalable web-based deployment
2024	S. Sivadharmaraj, Fatima Zehra Minni, Amiya Anand, Angelika Sahoo, Bheda Hemang	Real-Time Mock Interview Evaluation Using CNN	Built automated mock interview assessment system with multimodal analysis	CNN, DNN, OpenCV, NLP, speech analysis	High computational cost; video dependent	Limited structured LLM-based textual feedback
2024	K. Sampath, Kabirdoss Devi, T. V. Ambuli, S. Venkatesan	AI-Powered Employee Performance Evaluation Systems in HR Management	Developed AI-driven employee performance review system	Machine Learning, NLP, Explainable AI	HR domain specific	Not tailored for interview response evaluation
2023	Kuldeep Yadav, Animesh Seemendra, Abhishek Singhania, Sagar Bora, Pratyaksh Dubey, Varun Aggarwal	Interviewing the Interviewer: AI-generated Insights to Help Conduct Candidate-centric Interviews	Proposed post-interview interviewer feedback system	Conversational intelligence, behavioral metrics	Focuses on interviewer improvement	No direct candidate performance scoring
2023	Chuan Qin, Hengshu Zhu, Dazhong Shen, Ying Sun, Kaichun Yao, Peng Wang, Hui Xiong	Automatic Skill-Oriented Question Generation and Recommendation for Intelligent Job Interviews	Designed AI-based skill-oriented question generation system	Neural question generation, graph-enhanced recommendation	Limited to question generation	No answer evaluation or personalized feedback generation

Zhang et al. [1] evaluated Large Language Models such as GPT-3.5 and GPT-4 for asynchronous video interview assessment. Their study showed that LLMs can effectively analyze personality traits and interview performance with good contextual understanding. However, the work raised concerns regarding fairness, reliability, and rating consistency. It also lacked real-time interactive feedback and structured improvement suggestions.

Daryanto et al. [8] proposed Conversate, an AI-based interview practice platform that supports reflective learning through simulation and dialogic feedback. The system improved user engagement and helped candidates reflect on their responses. However, the study focused mainly on interview practice and training. It did not support real-time candidate evaluation or recruitment decisions.

Dixon et al. [5] developed an ML-driven recruitment framework for candidate assessment in online interviews. Their system integrated verification, language analysis, and behavioral assessment using machine learning techniques. Although the framework improved recruitment efficiency, it required complex infrastructure. It was not designed as a lightweight interview feedback system.

Hosseini et al. [4] introduced an avatar-based feedback system for mock interview training. Their study showed that avatar-driven interactions can reduce candidate anxiety and improve confidence. The system was effective in interview preparation scenarios. However, it lacked automated semantic response evaluation and recruitment-focused assessment.

Heimann and Schmitz-Wilhelmy [7] studied authenticity cues in job interviews and their relation to performance. Their work showed that verbal and nonverbal authenticity significantly influence interviewer perception. The study provided valuable behavioral insights for candidate evaluation. However, it depended on manual observation and lacked AI-based real-time assessment.

Luo et al. [10] developed a virtual reality interview simulator to study factors affecting candidate behavior. Their findings showed that realism and question type strongly influence interview anxiety and performance. The VR system improved interview training effectiveness. However, it required expensive infrastructure and lacked scalable web-based deployment.

Sivadharmaraj et al. [9] proposed a real-time mock interview evaluation system using CNN, speech analysis, and NLP. Their framework assessed facial expressions, speech patterns, and candidate responses. The system effectively supported automated mock interview analysis. However, it was computationally intensive and lacked structured LLM-based textual feedback.

2.1 Research Gap

Although significant progress has been made in AI-assisted interview systems, most existing studies focus on isolated functionalities such as mock interview training, interviewer coaching, question generation, multimodal behavior analysis, or enterprise-level recruitment screening [1]–[10]. Several systems have demonstrated effective speech analysis, avatar-based feedback, virtual reality simulations, and LLM-driven interview support [4], [8], [9], [10]; however, these solutions are often limited by high infrastructure cost, computational complexity, lack of real-time deployment, or restricted applicability to training environments rather than actual interview evaluation [5], [9], [10]. In addition, many existing frameworks either depend heavily on manual observation or fail to provide structured and actionable feedback to candidates after the interview [2], [7].

Despite recent advancements in Large Language Models and NLP-based assessment, there is still limited research on lightweight, web-based systems that integrate Speech-to-Text (STT), Natural Language Processing (NLP), and LLM-based semantic evaluation into a unified end-to-end framework for real-time interview interaction, structured candidate assessment, and automated audit report generation [1], [3], [8]. Therefore, there is a clear need for an intelligent, scalable, and practical interview feedback system that can deliver personalized, explainable, and role-specific feedback while reducing human bias and improving recruitment efficiency. This identified gap motivates the proposed work.

3. Methodology

The proposed AI-powered interview feedback generation system is designed as an integrated web-based framework that automates the complete interview evaluation process. The system combines Speech-to-Text (STT), Natural Language Processing (NLP), and Large Language Models (LLMs) to conduct role-specific interviews, analyze candidate responses, and generate structured feedback reports. The objective of the proposed system is to reduce manual effort, improve evaluation consistency, and provide meaningful feedback in real time.

3.1 Candidate Login and Interview Setup Module

The interview process begins with the candidate login and setup module. In this stage, candidates enter their personal and interview-related details such as name, company name, job role, experience level, interview type, and preferred topic. These details are collected through a user-friendly web interface. This module ensures personalized interview flow and provides the required context for question generation.

3.2 Dynamic Question Generation Module

Once the interview session is initialized, the dynamic question generation module creates relevant technical and behavioral interview questions based on the candidate's selected role and experience level. This module uses LLM-based prompt engineering to generate adaptive and context-aware questions instead of relying on fixed question banks. The dynamic nature of this module improves interview quality and ensures that the questions are aligned with the job requirements [3], [8].

3.3 Speech-to-Text Processing Module

During the live interview session, candidate responses are captured through microphone input. The speech input is first preprocessed to reduce noise and improve clarity. The cleaned audio is then passed to the Speech-to-Text engine, which converts spoken responses into text transcripts in real time. This module ensures accurate and efficient response capture, which is essential for downstream analysis.

3.4 NLP-Based Response Analysis Module

The transcribed responses are processed using Natural Language Processing techniques to evaluate communication quality and linguistic features. This module analyzes response clarity, sentence structure, fluency, coherence, logical flow, relevance to the question, and completeness of answer. It also extracts technical keywords and response patterns to assess communication effectiveness and subject knowledge [9], [12].

3.5 LLM-Based Semantic Evaluation Module

To enhance evaluation depth, the system incorporates an LLM-based semantic analysis module. This module performs contextual understanding of candidate responses by comparing them with expected answer patterns, job role expectations, and problem-solving criteria. It identifies strengths, weaknesses, missing concepts, and improvement areas. Compared to traditional rule-based systems, the LLM module provides more personalized, explainable, and role-aware feedback [1], [8], [14].

3.6 Audit Report Generation Module

The final stage of the proposed system is the audit report generation module. This module compiles all results into a structured performance report. The report includes competency-wise scores, overall performance rating, skill gap analysis, strengths, weaknesses, actionable recommendations, and an executive summary. A radar chart is also generated to visually represent candidate performance across key competencies such as technical skills, communication, confidence, and problem-solving ability.

The proposed methodology provides an integrated, scalable, and practical solution for intelligent interview assessment. By combining dynamic question generation, speech transcription, NLP-based analysis, semantic evaluation, and automated reporting, the system offers an effective framework for real-time interview feedback in modern digital recruitment workflows.

4. System Architecture and Workflow

The proposed AI-powered interview feedback generation system follows a modular and lightweight web-based architecture designed to support real-time interview interaction, automated response analysis, and structured report generation. The system integrates frontend interaction, backend processing, speech-to-text conversion, LLM-based question generation, semantic response evaluation, and feedback reporting into a unified framework. The architecture ensures low latency, scalability, and effective candidate assessment.

4.1 System Architecture

The overall system architecture consists of multiple interconnected layers that work together to automate the interview evaluation process, as illustrated in **Fig. 2**. The process begins at the frontend interface, where the candidate accesses the web application and initializes the interview session. The frontend, developed using React and TypeScript, provides functionalities such as interview setup, question display, audio response submission, and report visualization.

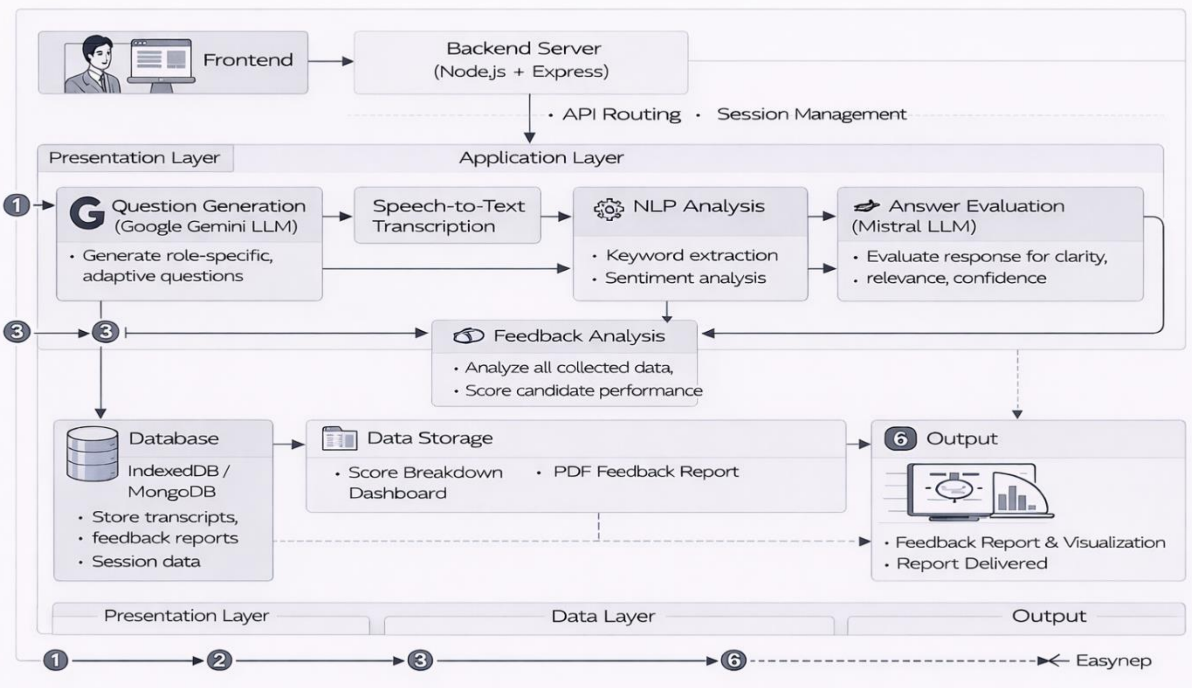

Fig. 2: System Architecture of AI-Powered Interview Feedback Generator

The frontend communicates with the Node.js and Express.js backend server, which acts as the central controller of the system. The backend manages API routing, session handling, prompt construction, and score aggregation.

Based on candidate profile and job role, the backend interacts with the Gemini API to dynamically generate role-specific technical and behavioral interview questions. This ensures adaptive and context-aware interview interaction.

During the interview session, candidate responses are captured through the audio recording module. The speech input is processed and converted into text using the Speech-to-Text engine. The generated transcripts are then passed to the backend for further analysis. To perform deep semantic evaluation, the backend communicates with the Mistral API, which analyzes candidate responses based on relevance, technical correctness, communication quality, and role suitability.

The processed insights from both NLP and LLM-based semantic evaluation are passed to the feedback generation module. This module identifies candidate strengths, weaknesses, missing concepts, and performance gaps. It also computes competency-wise scores and prepares actionable recommendations. The final interview results are stored in IndexedDB for session persistence and later retrieval. The structured performance report is then displayed through the report interface, enabling both candidates and recruiters to review detailed feedback.

4.2 Workflow of the Proposed System

The workflow of the proposed system describes the sequence of operations involved in conducting the interview and generating structured feedback, as shown in **Fig. 3**. The process begins when the candidate starts the interview session through the web interface. Based on the selected job role and interview type, the system generates role-specific questions using Gemini and Mistral APIs. Once a question is displayed, the candidate provides the response through microphone input. The system records the audio response and processes it using the Speech-to-Text engine to convert speech into text transcripts. This ensures that spoken answers can be accurately analyzed by downstream modules.

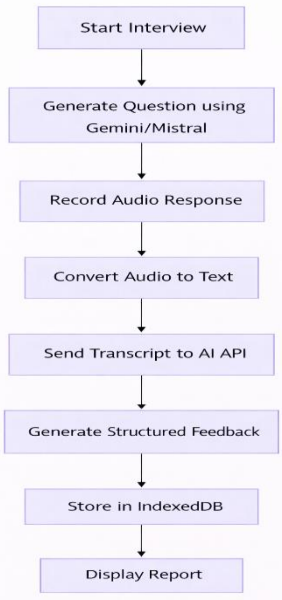

Fig. 3: Interview Process Flow

The transcribed response is then sent to the AI processing layer for semantic evaluation. The LLM module analyzes the candidate's response by checking answer relevance, logical flow, communication quality, technical correctness, and confidence indicators. Based on this analysis, the system generates structured feedback that includes strengths, weaknesses, suggestions for improvement, and overall performance score.

After feedback generation, the system stores the interview session data and report details in IndexedDB for persistence. Finally, the complete performance report is displayed to the candidate through the report dashboard. The workflow ensures smooth module interaction, automated assessment, and real-time feedback generation in an efficient and scalable manner.

5. Implementation

The proposed AI-powered interview feedback generation system was implemented as a lightweight web-based application using a modern full-stack architecture. The system integrates a React.js frontend, Node.js and Express.js backend, Gemini and Mistral APIs, Speech-to-Text processing, and IndexedDB storage to support real-time interview interaction and automated feedback generation.

The frontend was developed using **React.js**, **TypeScript**, and **Vite** to provide a responsive and user-friendly interface for candidate login, interview setup, question display, audio response recording, and report visualization. React's component-based architecture improved UI modularity and maintainability.

The backend was implemented using **Node.js** and **Express.js**, which handle session management, API routing, prompt construction, transcript processing, score aggregation, and report generation. The backend acts as the central controller for coordinating all interview modules.

The system integrates the **Gemini API** to generate dynamic role-specific interview questions and the **Mistral API** to perform semantic evaluation of candidate responses. The Web Speech API was integrated to convert candidate audio responses into text transcripts in real time, enabling efficient downstream NLP and LLM-based semantic evaluation.

For data storage, **IndexedDB** was used to store candidate session details, transcripts, evaluation scores, and final reports. IndexedDB was selected because it supports fast local storage and lightweight deployment without requiring a dedicated database server.

5.1 Technology Stack

Component	Technology Used
Frontend	React, TypeScript
Backend	Node.js, Express
Speech Recognition	Web Speech API
AI Evaluation	Gemini API, Mistral API
Storage	IndexedDB
Deployment	Local/Web-based environment

6. Results and Discussion

To evaluate system performance, the proposed framework was tested across multiple mock interview sessions involving different job roles.

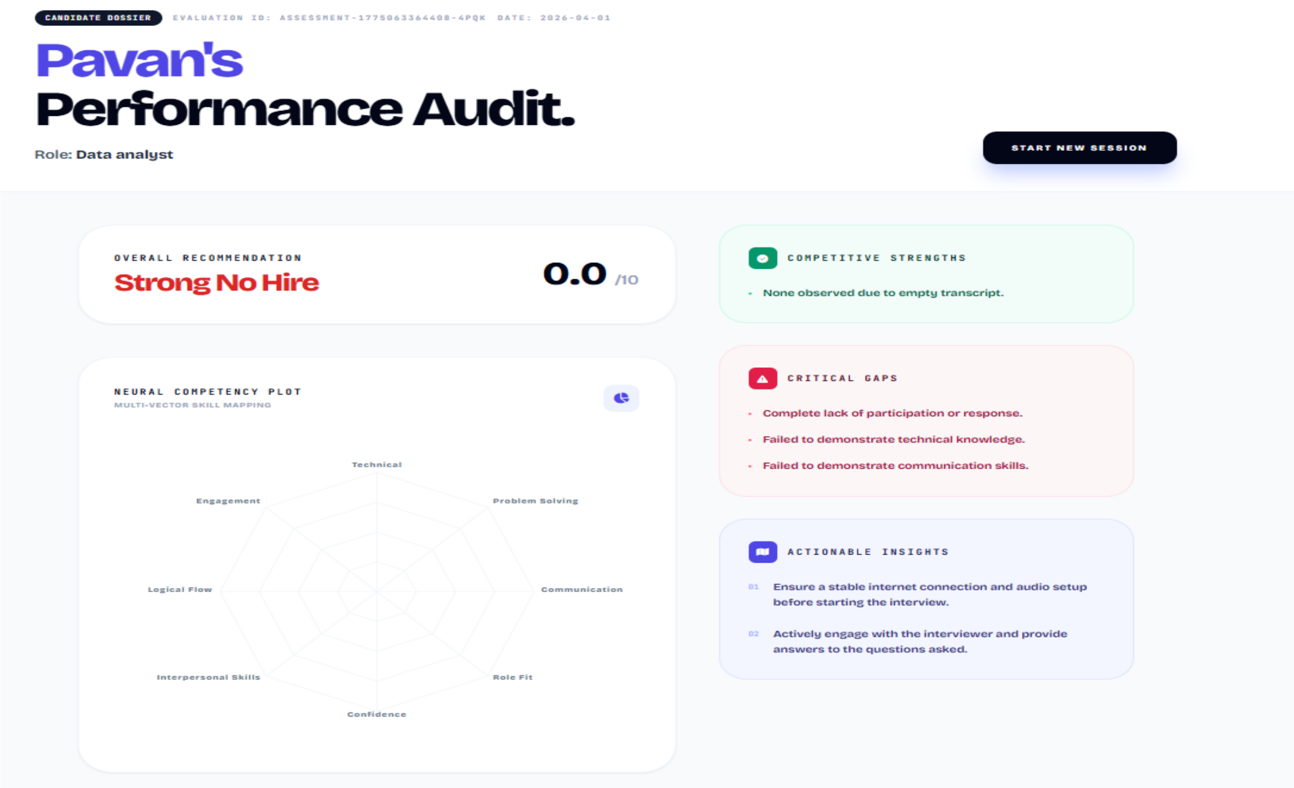

Fig. 4. Generated performance dashboard showing recommendation, scores, and competency analysis.

The average question generation latency was observed to be approximately 2–3 seconds, while semantic feedback generation required 3–5 seconds depending on response length. Speech transcription accuracy was satisfactory under normal speaking conditions, with reliable performance in low-noise environments. These observations confirm that the system is suitable for practical real-time interview assessment.

As shown in **Fig 4** the generated performance dashboard presents overall recommendation, competency-wise scores, radar chart visualization, strengths, critical gaps, and actionable suggestions. The dashboard clearly highlights candidate performance across technical skills, communication, logical flow, confidence, and engagement, enabling easy interpretation of results.

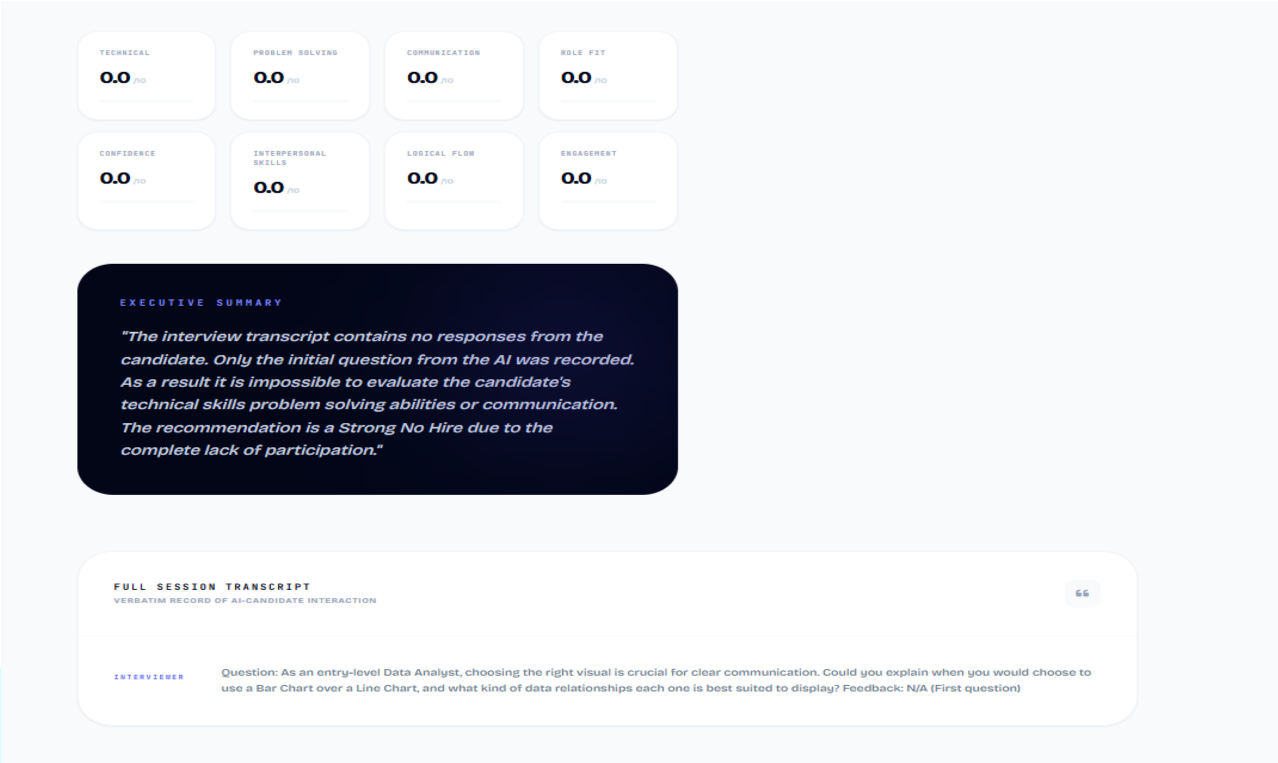

Fig. 5. Executive summary and interview transcript generated by the system.

As illustrated in **Fig. 5**, the system also generates an executive summary and stores the complete interview transcript. The executive summary provides concise performance insights, while the transcript ensures transparency and traceability of the evaluation process.

The Web Speech API provided satisfactory speech transcription under normal conditions, and the LLM-based semantic evaluation module effectively analyzed response relevance, communication quality, and technical correctness. Overall, the results demonstrate that the proposed system provides an effective and practical solution for real-time interview feedback generation.

7. Conclusion

This paper presents an AI-powered automated interview feedback generation system that integrates Speech-to-Text, Natural Language Processing, and Large Language Models for real-time, structured candidate evaluation. The proposed approach effectively addresses limitations of traditional interviews, including subjectivity, delayed feedback, and scalability issues. By enabling dynamic question generation, semantic response analysis, and automated report generation, the system ensures efficient end-to-end interview assessment. Experimental results demonstrate its ability to deliver consistent evaluations, meaningful insights, and personalized feedback, thereby reducing recruiter workload and enhancing candidate learning. Overall, the proposed framework provides a scalable and practical solution for modern AI-driven recruitment systems.

8. Future Enhancements

- Multimodal Behavioral Analysis: Integrate facial expression and gesture recognition using deep learning techniques (e.g., CNNs and transformer-based vision models) to enhance the accuracy of behavioral and emotional assessment during interviews.
- Scalable and Intelligent System Design: Deploy the system on cloud platforms (e.g., AWS or Google Cloud) with distributed databases and incorporate adaptive question generation using reinforcement learning to improve scalability, personalization, and real-time performance.
- Multilingual and Explainable AI Integration: Extend support for multiple languages using advanced multilingual NLP models and incorporate explainable AI (XAI) techniques to provide transparent, interpretable feedback for both recruiters and candidates.

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