Mock Interviewer

Dr. D Kirubha[1], Anneshan Choudhury[2], Prakhar Srivastava[3], Prashant Kumar Singh[4]

[1]HOD, Department of CSE, Raja Rajeswari college of Engineering, Bengaluru, Karnataka, India.
[2,3,4] Department of CSE, RajaRajeswari college of Engineering, Bengaluru, Karnataka, India.

Abstract: *Rapid growth in digital recruitment has led to the need for scalable, objective and intelligent interview preparation (and assessment) systems. The majority of traditional interview techniques rely on human responses, which are often inconsistent and subjective. However, only a few candidates can provide such feedback without difficulty. The paper presents AI Interviewer, a web-based interview preparation tool that assists candidates with automated interview practice, detailed performance analysis, resume optimization, and ATS compatibility assessment. Real-time video and voice interviews, AI-led role specific questions, live transcription, and natural language-based evaluation of candidate responses are all supported by the platform. Moreover, it includes an integrated resume analyzer that uses ATS for scoring tasks and provides feedback, as well as a resume builder that can generate resumes tailored to job functions. Firebase-powered cloud storage is used to store all analytical reports and historical performance metrics. This system emphasizes the importance of being comprehensible, impartial and easily applicable. Using real-life scenarios on platforms, the effectiveness of using multimodal assessment and dashboard-based feedback has been demonstrated to enhance candidate preparedness. In today's recruitment ecosystems, the platform is a complete AI-powered solution.*

Keywords: *Artificial Intelligence, AI Interviewer, Multimodal Learning, Resume Analyzer, ATS Scoring, and Interview Automation.*

I.INTRODUCTION

For many recruitment processes, interview preparation is crucial, especially for students and early-career professionals. Misfits in preparation methods, such as mock interviews with peers or mentors, are frequently impeded by their lack of availability and subjectivity, as well as the absence of structured feedback. In addition, the use of applicant tracking systems during resume screening has created more complications for those without knowledge of ATS optimization criteria.

Advances in artificial intelligence have made it possible to create intelligent systems that can automate human-centric tasks such as evaluation, feedback generation and performance analysis. Several AI-powered interview systems have gained attention for their ability to offer reliable, consistent, and data-driven assessments. Many existing solutions are either too automatized or do not offer transparency and practical integration.

This article discusses the integration of AI Interviewer, a comprehensive interview preparation tool that assesses candidates through standardized tests using multiple modalities. This is to help candidates improve their interview performance and resume quality by providing clear, AI-generated feedback.

II. LITERATURE SURVEY

A. Artificial Intelligence in Recruitment (2018–2024)

The adoption of artificial intelligence in recruitment has increased significantly due to the demand for scalable and efficient hiring processes. Early AI-based recruitment systems primarily focused on automating resume screening through keyword matching and rule-based filtering. While these systems reduced manual effort, they lacked semantic understanding and often produced inconsistent outcomes. Prior studies highlighted that AI can enhance decision-making in talent acquisition by providing data-driven insights rather than replacing human judgment entirely, while also warning about risks related to bias and over-reliance on automation [1], [2]. These findings indicate that although AI improves operational efficiency, ethical considerations and transparency remain unresolved challenges in AI-driven recruitment systems.

B. Automated and AI-Based Interview Systems (2019–2024)

Automated interview systems emerged as an extension of AI-driven recruitment to standardize candidate evaluation. Initial approaches relied on text-based questionnaires and predefined scoring rules, limiting their ability to assess communication skills and behavioural traits. With advances in speech processing and computer vision, researchers began

exploring video-based interview analysis. Multimodal signals such as facial expressions, vocal prosody, and response timing have been shown to correlate strongly with interview performance [3]. More recent studies employing deep learning models demonstrated improved prediction accuracy by combining audio and visual features [4]. Despite these advances, most automated interview systems operate as black-box models, offering limited interpretability, which raises concerns related to candidate trust and regulatory compliance.

C. Multimodal Learning for Candidate Assessment (2020–2024)

Multimodal learning integrates information from multiple sources to model complex human behaviour more accurately. In interview assessment, multimodal systems combine textual, speech, and visual cues to capture both verbal and non-verbal communication. Fusion-based multimodal models have been shown to outperform unimodal approaches across various human-centred tasks [5]. Applied to interview datasets, multimodal fusion techniques significantly improve candidate classification accuracy compared to text-only models [6]. However, existing multimodal interview research largely focuses on recruiter-side automation and provides limited support for candidate-facing feedback, fairness analysis, or long-term performance tracking.

D. Resume Analysis and Applicant Tracking Systems (ATS) (2017–2024)

Applicant Tracking Systems are widely used to filter resumes before human review. Traditional ATS platforms rely heavily on keyword matching and formatting constraints, which can result in qualified candidates being rejected due to minor structural issues. Studies examining fairness in algorithmic resume screening have highlighted how keyword-based systems may disadvantage certain candidate groups [7]. Recent approaches apply natural language processing and embedding-based similarity models to improve resume–job matching, achieving higher agreement with human evaluators [8]. Despite these improvements, most ATS tools fail to provide actionable feedback to candidates and remain poorly integrated with interview preparation systems.

E. Bias, Fairness, and Explainability in AI Hiring (2020–2024)

Bias and fairness have become central concerns in AI-based hiring systems. Large-scale analyses of commercial algorithmic hiring tools found limited empirical evidence supporting claims of bias reduction [9]. Systematic reviews further indicate that many AI recruitment systems replicate historical biases due to biased training data and opaque decision mechanisms [10]. To mitigate these risks, researchers propose fairness-aware learning techniques such as reweighting and adversarial debiasing, along with explainable artificial intelligence methods including SHAP and LIME. Explainability has been emphasized as essential for accountability and trust in high-stakes decision-making systems such as hiring [11]. However, practical integration of fairness-aware and explainable mechanisms into candidate preparation platforms remains limited.

F. Research Gap and Motivation

The reviewed literature reveals several gaps in existing AI-driven recruitment and interview systems. Most current solutions prioritize recruiter-side automation over candidate preparation and skill development. Multimodal interview models frequently lack interpretable and actionable feedback mechanisms for candidates. Resume analysers and applicant tracking systems are rarely integrated with interview preparation platforms, resulting in fragmented candidate experiences. Furthermore, longitudinal performance tracking and dashboard-based analytics remain underexplored. These limitations motivate the development of an integrated AI Interviewer platform that combines multimodal interview assessment, explainable feedback, resume optimization, ATS scoring, and persistent performance tracking.

III. PROBLEM DEFINITION AND CONTRIBUTIONS

A. Problem Definition and Contribution

The absence of structured interview practice and actionable feedback is a common issue for candidates. Additionally, even though the candidate has excellent skills, ATS systems often reject resumes due to mismatches in formatting and keywords. Present-day artificial intelligence interview software seldom integrates job assessment with resumption checking and persistent performance tracking.

B. Contributions

The key takeaways from this research are:

Creation of a practical, online AI Interviewer application.

The assessment pipeline of interviews that utilizes text, voice feedback, and video.

Generating quantifiable performance metrics through automated reporting.

Combination of an ATS-based resume analyzer and dynamic resume builder.

Continuous dashboard-based performance tracking via cloud backend.

IV. PLATFORM OVERVIEW

The AI Interviewer platform is a tool that assists both students and job seekers in improving their resumes by conducting practice interviews. Its core modules include:

AI Video Interviewer.
Interview Analytics Dashboard.
Resume Analyzer with ATS Scoring.
Dynamic Resume Builder.

By using a password-protected login system, users can access all features on one interface with ease. The overall interface of the AI Interviewer platform is shown in Fig. 1.
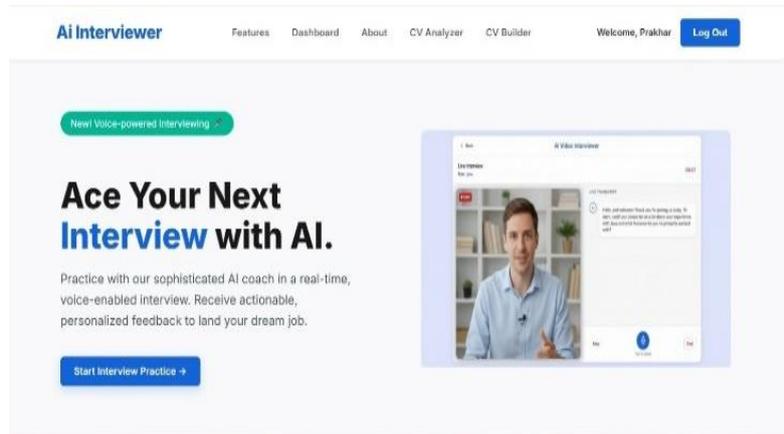

Fig. 1. Landing page of the AI Interviewer platform

V. AI VIDEO INTERVIEWER MODULE

The AI Video Interviewer enables candidates to participate in real-time mock interviews. After selecting a specific job role, the system generates interview questions tailored to each role. The camera and microphone of the device are utilized for interviewing, with both voice and video input available.

While being interviewed, the system records the number of questions answered, total interview duration, average response time, and word count per response.

Semantics analysis can be conducted through live transcription, which transforms spoken responses into text form. Candidates interact with the system through a real-time video interview interface, as shown in Fig. 2.
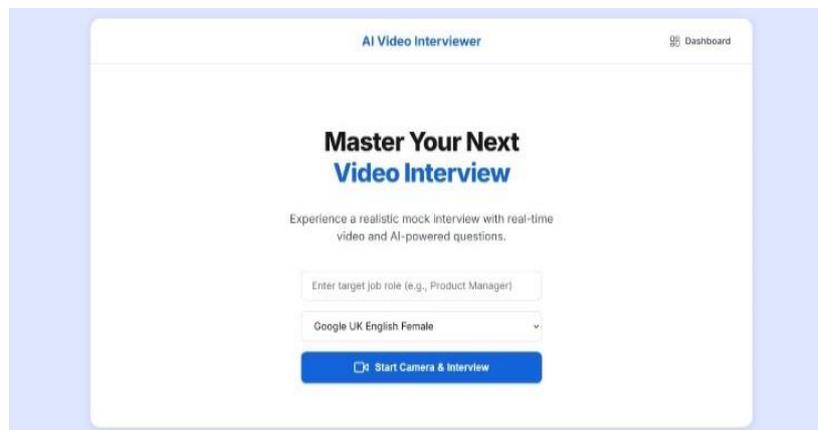

Fig. 2. AI video interview interface used for mock interviews

VI. ANSWER EVALUATION AND FEEDBACK GENERATION

By using natural language processing techniques, candidates can be evaluated on their answers' suitability, clarity, and technical expertise. The linguistic traits of keyword usage, coherence, and response length are examined.
This analysis is used to generate a detailed summary of system performance, which includes:
Overall interview assessment.
Identified strengths.
Areas requiring improvement.
Personalized suggestions.

This feedback is meant to be interpreted and used as an example. During the interview, candidate responses are captured and transcribed in real time, as shown in Fig. 3.

After gathering all answers from candidate, a report is generated to check the overall performance. The system records the number of questions answered, total interview duration, average response time, and word count per response as shown in Fig. 4.
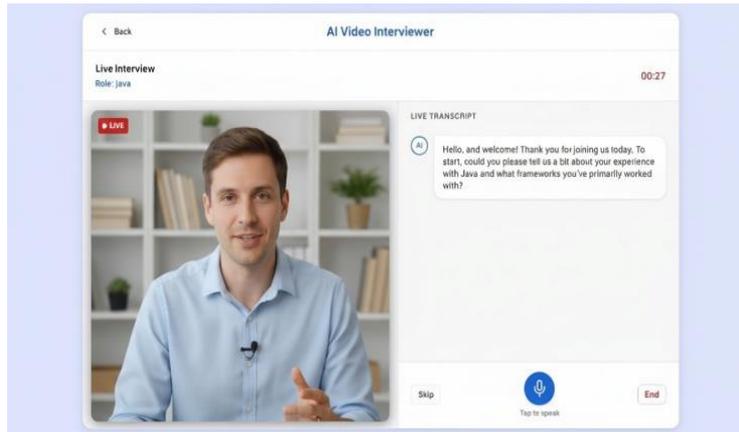
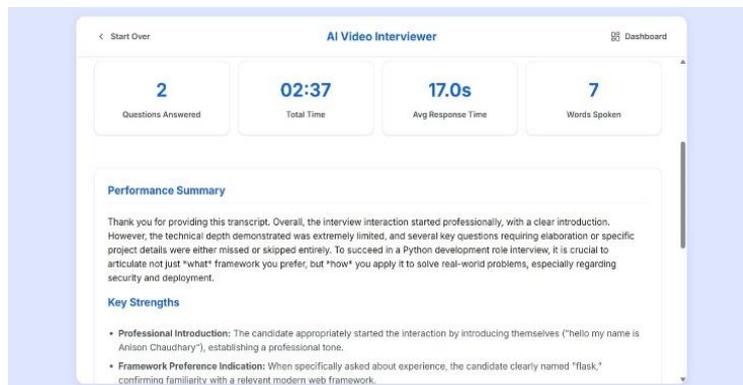*Fig. 3. Interview session with real-time question and response capture*

Fig. 4. Analysed Report

VII. INTERVIEW DASHBOARD AND PERFORMANCE TRACKING

The Interview Dashboard provides users with historical analytics and performance trends. Sessions are recorded with timestamps and metrics for each completed interview. Users can refer back to detailed reports and track improvements over time.

Continuous monitoring facilitates self-assessment and ongoing skill development. The dashboard provides longitudinal performance tracking, as illustrated in Fig. 5.
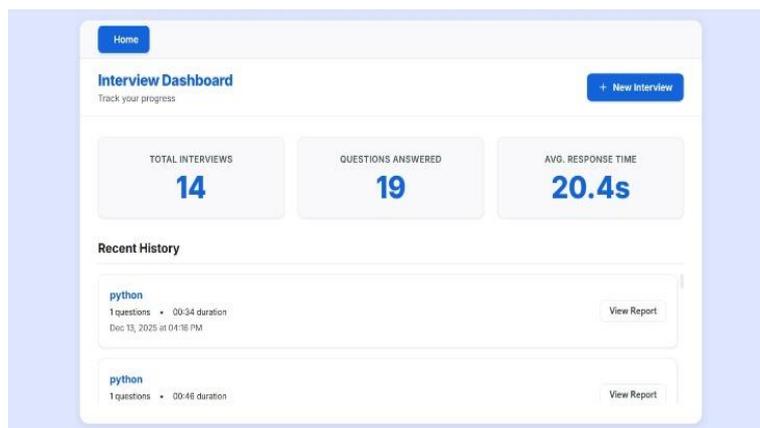

Fig. 5. Interview analytics dashboard displaying historical performance metrics

VIII. RESUME ANALYZER WITH ATS SCORING

The Resume Analyzer enables candidates to upload resumes in PDF or image formats. The system gathers all textual and structural data, compares it against an optional job description. A score of ATS compatibility is determined by the following factors: Keyword, relevance, Section structure and Formatting compliance.

By providing detailed feedback on strengths and weaknesses, candidates can enhance their resumes' effectiveness. The resume analyzer evaluates uploaded resumes and generates an ATS score Fig. 6.
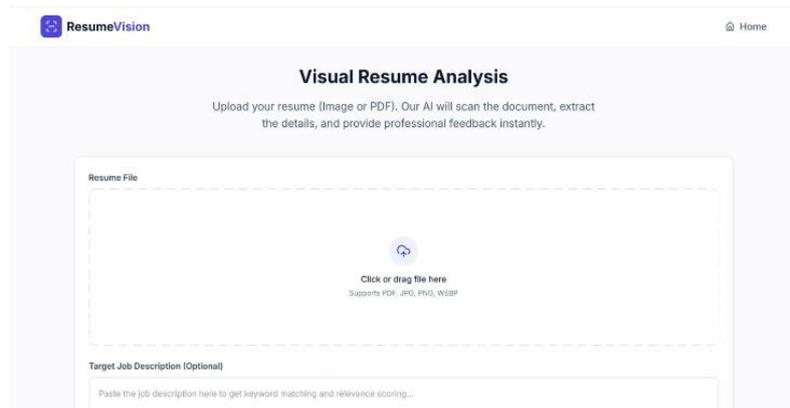
Fig. 6. Resume analyzer generating ATS score and feedback

IX. DYNAMIC RESUME BUILDER

By utilizing guided input and AI-assisted content generation, the Dynamic Resume Builder empowers candidates to construct professional resumes. By customizing resumes to specific job descriptions and exporting the finalized resume as a PDF, users can make it compatible with ATS.

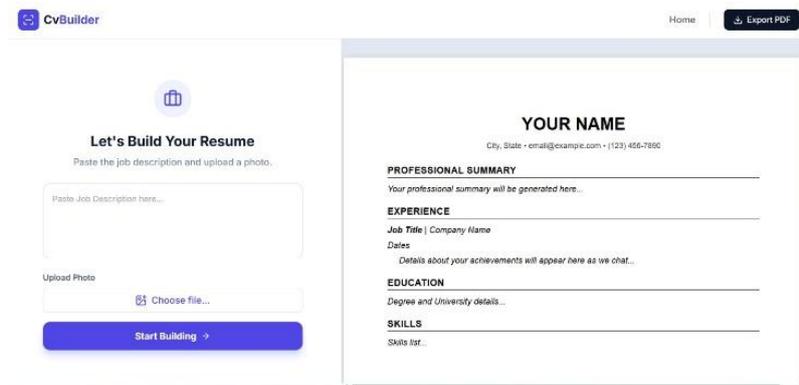Candidates can generate job-specific resumes using the builder shown in Fig. 7.

Fig. 7. Dynamic resume builder interface

X. BACKEND IMPLEMENTATION USING FIREBASE

The backend of the platform is built upon Firebase. Firebase Authentication handles secure user login, while Cloud Firestore stores interview reports, dashboard metrics, and resume analysis results. Uploading resumes and related assets to Firebase Storage is the means of handling them.

With the cloud architecture, users can rely on scalability, real-time data synchronization, and reliable persistence of their data.
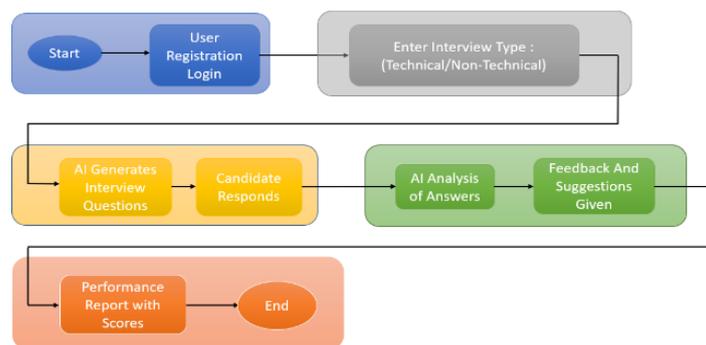
XI. SYSTEM WORKFLOW

Fig. 8. System workflow and block diagram of the AI Interviewer platform

The system workflow starts with the user authentication process, followed by interview type selection. The AI Interviewer formulates inquiries, records responses from potential candidates, implements AI-based assessment, and produces statements. On the dashboard, you can view your performance reports. Despite being distinct, both resume analysis and building modules are integrated into the same user profile. The complete system workflow is illustrated in Fig. 8.

XII. ETHICAL CONSIDERATIONS

The platform prioritizes transparency and user acceptance. Data usage is communicated to candidates, and sensitive data is stored in a secure environment. Explained feedback mechanisms reduce black-box decision-making and fairness-aware design principles minimize bias.

XIII. LIMITATIONS

The system's performance is presently dependent on internet connectivity and device hardware quality. Model accuracy can differ depending on the accent and domain. Further, extensive analysis is necessary to generalize conclusions.

XIV. FUTURE SCOPE

Future enhancements include support for multiple languages in an interview, emotion-based feedback, adaptive questioning, and analytics from the recruiter. Further integration with learning management systems and more advanced fairness auditing mechanisms is also in the works.

XV. CONCLUSION

AI Interviewer, a platform that helps with interview preparation and resume optimization, was presented in this paper. It is entirely powered by AI. With its integration of multimodal interview analysis, ATS-based resume assessment and persistent performance tracking reporting, the system is both practical as well as scalable for modern recruitment purposes. The platform demonstrates how AI can improve candidate readiness while maintaining transparency and usability.

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