iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** X **Month of publication:** October 2026

DOI: https://doi.org/10.22214/ijraset.2026.85512

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue X Oct 2026- Available at www.ijraset.com

Interview IQ³: An AI-Powered Intelligent Hiring Platform for Resume Analysis, Adaptive Interview Practice and Recruiter Workflow Management

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Abstract: ***Recruitment is still slow and uneven: recruiters read large numbers of resumes, applicant tracking systems filter by keywords, and candidates receive little feedback after an interview. Existing tools cover one stage of hiring each, so recruiters and candidates must use separate platforms. This paper presents Interview IQ³, an artificial intelligence (AI) based hiring platform that joins resume analysis, adaptive interview practice and recruiter workflow management in one web application. A Llama 3 language model accessed through an API reads the text of an uploaded resume and returns an applicant-tracking-system (ATS) score, missing keywords, strengths, weaknesses and suggested roles. An adaptive interview generates questions from the resume, the target role, the experience level and a company-specific mode, accepts answers by text or voice, and evaluates them for technical accuracy, confidence, fluency, grammar and relevance with BERT and Sentence Transformer models. Companies create jobs and assessment rounds, and recruiters compare AI-generated reports and shortlist candidates. The system is built with React, Node.js, Express, MongoDB and Firebase. The architecture, scoring rule and prototype are described, and a reproducible evaluation plan is given.***

Keywords: ***Recruitment Automation, Resume Analysis, Adaptive AI Interview, Natural Language Processing (NLP), Semantic Answer Evaluation, Large Language Model (LLM), Candidate Assessment, Interview Preparation.***

I. INTRODUCTION

Hiring has become more competitive for both sides. A company advertising a post may receive hundreds of resumes, and the recruiter must screen them, schedule interviews and compare candidates by hand. A graduate, in turn, prepares for interviews with printed question lists or separate practice sites and, after a real interview, usually learns only whether the application succeeded. Neither side gets a clear account of why a decision was made.

Each part of this problem has been addressed, but only by a separate solution. Applicant tracking systems filter resumes mostly by keywords and may overlook a qualified candidate who words a skill differently. Studies of AI in recruitment discuss screening and matching [1], [2], and hiring tools have been questioned for a lack of validation and of transparency [3]. Language models can now understand the meaning of text [4], [6] and generate it [8], [9], but they are not tied to a recruiter's workflow or to a candidate's practice history. A user who needs all of these must use several tools whose data are not shared.

This paper presents Interview IQ³, a unified *AI-based hiring platform* for four kinds of user: administrators, companies, recruiters and candidates. Its *AI resume intelligence* module analyses a resume, its *adaptive AI interview* module generates and evaluates questions, and its *recruiter workflow* module lets a company configure jobs and rounds and compare candidates on AI-generated reports. The same account therefore serves a candidate who is practising and a recruiter who is hiring.

II. LITERATURE SURVEY

1) P. van Esch, J. S. Black and J. Ferolie, "Marketing AI Recruitment: The Next Phase in Job Application and Selection", Computers in Human Behavior (2019). The study examines how job seekers react to AI in recruiting and finds that the novelty of AI recruitment increases the likelihood of applying. It shows that AI in hiring is acceptable to candidates, but it is not a platform that screens, interviews and gives feedback. [1]

2) J. Malinowski, T. Keim, O. Wendt and T. Weitzel, "Matching People and Jobs: A Bilateral Recommendation Approach", HICSS (2006). The paper treats matching as two selections, in which both the person's and the employer's side must be considered. It supports candidate–job matching but gives no interview preparation or response evaluation. [2]

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3) M. Raghavan, S. Barocas, J. Kleinberg and K. Levy, "Mitigating Bias in Algorithmic Hiring: Evaluating Claims and Practices", ACM FAT* (2020). The authors document what vendors of algorithmic pre-employment assessments disclose about their development and validation and evaluate their bias-mitigation claims. The work motivates transparent and validated scores, but it is an analysis of practice and not a hiring platform. [3]

4) J. Devlin, M.-W. Chang, K. Lee and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding", NAACL-HLT (2019). BERT learns contextual representations of text and improves many language understanding tasks after fine-tuning. It supports meaning-based analysis of candidate answers, but it is a general model and not an interview system. [4]

5) P. Rajpurkar, J. Zhang, K. Lopyrev and P. Liang, "SQuAD: 100,000+ Questions for Machine Comprehension of Text", EMNLP (2016). A dataset of more than 100,000 questions on Wikipedia passages is introduced for reading comprehension. It underlies question-answering models but does not address interviews or hiring. [5]

6) N. Reimers and I. Gurevych, "Sentence-BERT: Sentence Embeddings Using Siamese BERT-Networks", EMNLP-IJCNLP (2019). Sentence-BERT produces sentence embeddings that can be compared by cosine similarity, which makes semantic comparison of two texts fast. It suits resume matching and answer evaluation, but the paper gives no recruitment application. [6]

7) Y. Zhang and B. Wallace, "A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification", IJCNLP (2017). A convolutional network for sentence classification is analysed under different settings, and practical guidance is given. It remains a classification study and does not evaluate longer, open answers. [7]

8) T. B. Brown et al., "Language Models Are Few-Shot Learners", NeurIPS (2020). A large language model performs many tasks from a few examples in its prompt, without task-specific training. It shows that question generation and feedback writing are possible, but it does not control quality for a hiring setting. [8]

9) H. Touvron et al., "LLaMA: Open and Efficient Foundation Language Models", arXiv (2023). The LLaMA models are open foundation language models trained on public data. They are the first of the family to which the Llama 3 model used here belongs, but the paper does not concern recruitment. [9]

10) Y. Qin et al., "Tool Learning with Foundation Models", arXiv (2023). The work studies how foundation models can use external tools to carry out complex tasks. It supports AI assistants that automate workflow steps, but it gives no hiring system. [10]

11) P. Lewis et al., "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks", NeurIPS (2020). Retrieval-augmented generation grounds a language model's output in retrieved documents. It offers a way to base interview questions and feedback on a curated question bank, which is planned here as future work. [11]

12) T. Wolf et al., "Transformers: State-of-the-Art Natural Language Processing", EMNLP System Demonstrations (2020). The Transformers library gives a common interface to pre-trained language models and was the basis of the Hugging Face model hub. It makes models such as BERT and Sentence Transformers easy to use, but it is infrastructure and not a hiring system. [12]

III. RESEARCH GAP

The surveyed works provide screening, matching or language-understanding components, as summarised in Table I, but not a platform that serves recruiters and candidates together. The following gaps remain.

A. Separate Tools for Separate Stages

Resume screening, job matching, interview practice and recruiter workflow are offered by different tools that do not share data [1], [2]. No surveyed work links the resume analysis, the interview and the recruiter's report of one person.

B. Keyword Matching Instead of Meaning

Language models can compare texts by meaning [4], [6], yet screening is commonly keyword-based, so a skill described in different words may be missed.

C. Scores without Explanation

Pre-employment algorithms are often adopted without published validation [3]. A candidate who receives only a selection or rejection cannot identify the skill to improve, and a recruiter cannot see why a score was given.

D. Preparation Separated from Hiring

Practice sites prepare candidates for generic interviews, whereas a company hires for a particular role. The practice and the official assessment should use the same evaluation.

TABLE I.
CAPABILITIES OF RELATED WORK AND INTERVIEW IQ³ (YES = PROVIDED; PART. = PARTIALLY OR AS AN ENABLING TECHNIQUE; – = NOT DESCRIBED)

Work	Resume screening	Job matching	Semantic answer evaluation	Interview question generation	Candidate feedback	Recruiter workflow
[1]	Part.	Part.	–	–	–	Part.
[2]	–	Yes	–	–	–	–
[3]	Part.	–	–	–	–	–
[4], [5], [6]	–	–	Part.	–	–	–
[7]	–	–	Part.	–	–	–
[8], [9]	–	–	–	Part.	Part.	–
[10], [11]	–	–	–	Part.	–	Part.
Interview IQ³	Yes	Yes	Yes	Yes	Yes	Yes

IV. PROBLEM STATEMENT

Recruiters and candidates lack a unified, low-cost platform that, through one account, (i) analyses a resume by meaning and reports an ATS score with specific suggestions, (ii) generates interview questions for a role and a company and evaluates the answers with feedback, (iii) lets a company configure jobs and assessment rounds and compare candidates on AI-generated reports, and (iv) keeps a history of resumes, interviews and reports that can be reviewed by the right user only.

V. OBJECTIVES

1) To provide secure registration and login with role-based access for administrators, companies, recruiters and candidates.
2) To analyse an uploaded resume with a language model and report an ATS score, missing keywords, strengths, weaknesses and suggested roles.
3) To generate interview questions from the resume, role, experience level and company mode, and to adapt their difficulty to the answers.
4) To evaluate answers given by text or voice and return a score with feedback and improvement suggestions.
5) To let companies create jobs and rounds, and recruiters compare candidates, shortlist them and record the outcome.
6) To store resumes, interviews and reports for later review, and to define a reproducible evaluation.

VI. METHODOLOGY

A. System Architecture

Interview IQ³ has three tiers, as shown in Fig. 1. The four kinds of user work through a React.js web application styled with Tailwind CSS, which offers a dashboard for each role, resume upload, an interview room, history and report pages. A Node.js and Express.js server exposes REST routes for authentication, companies, recruiters, candidates, interviews, resumes and administration. The server stores data in MongoDB Atlas, relies on Firebase Authentication for sign-in, and calls the AI models for resume analysis and interview evaluation. The frontend is deployed on Netlify and the backend on Render.

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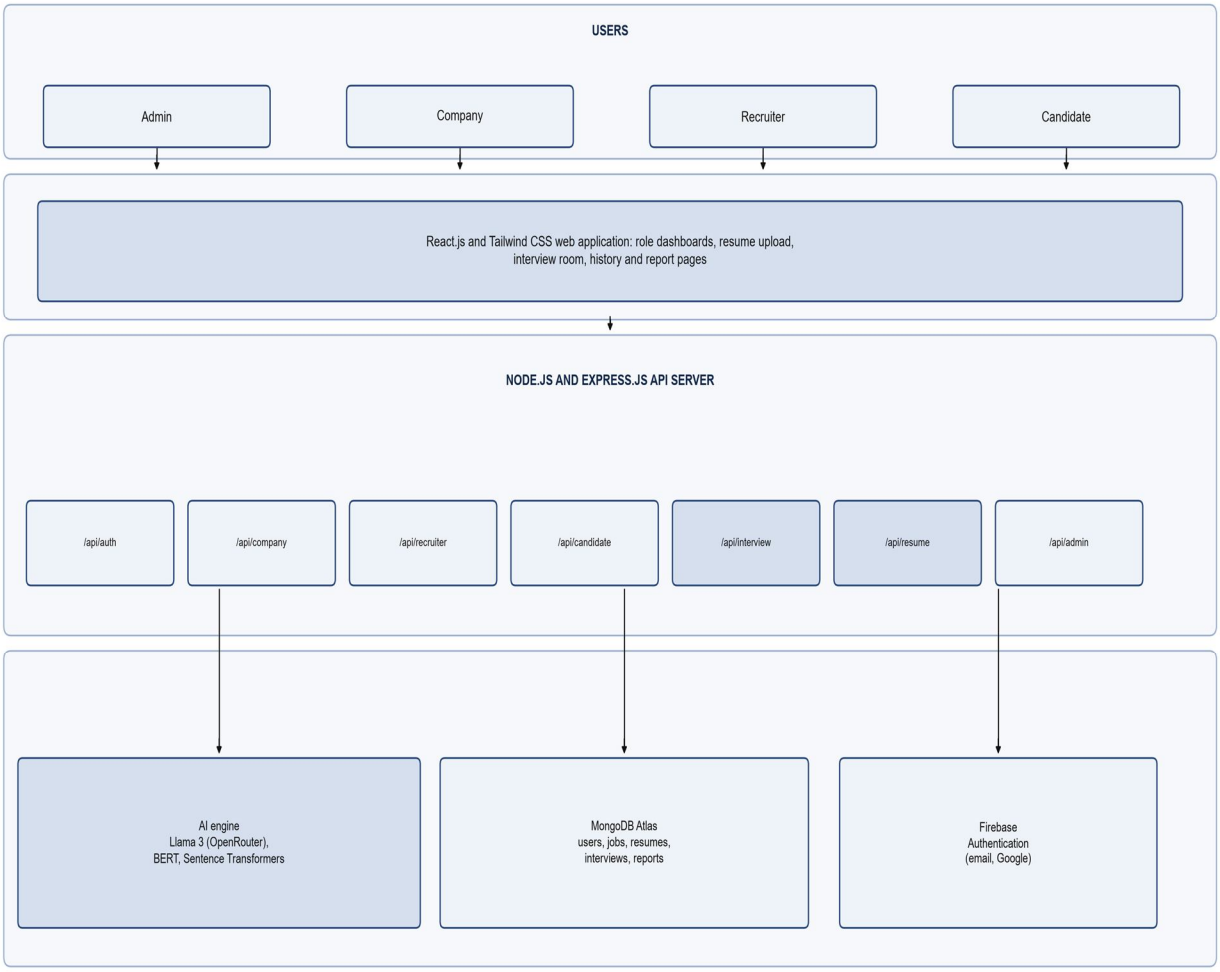


Fig. 1. Architecture of Interview IQ³: users, React frontend, Express API server, and the AI engine, MongoDB and Firebase services.

B. Users, Roles and Security

Table II lists the four roles. After login a user is redirected to the dashboard of the role and can open only the modules assigned to it (role-based access control). The backend stores passwords as bcrypt hashes and returns a signed JSON Web Token that expires after seven days; the role of a new account defaults to candidate. The platform also supports Google sign-in through Firebase Authentication.

TABLE II.
ROLES AND PRINCIPAL FUNCTIONS

Role	Principal functions
Admin	Verify company accounts, manage users and recruiters, monitor the platform
Company	Register, create a company profile, create jobs, configure eligibility and assessment rounds
Recruiter	Schedule rounds, review AI reports, compare and shortlist candidates, update status
Candidate	Upload a resume, take practice and official interviews, view feedback, history and reports

C. Backend and Data

The API is organised in the route groups of Table III. MongoDB holds the entities of Table IV; a candidate record carries the AI score and the recruitment status, which is updated through a protected route, and the recruiter dashboard reads the number of jobs, candidates, shortlisted candidates and hired candidates directly from the database.

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TABLE III.
API ROUTE GROUPS

Route	Purpose
/api/auth	Registration and login
/api/company	Company profile and recruitment configuration
/api/recruiter	Candidate lists, dashboard counts and status update
/api/candidate	Candidate profile and progress
/api/interview	Interview sessions, evaluation and feedback
/api/resume	Resume upload and analysis
/api/admin	Administration and approval

TABLE IV.
PRINCIPAL DATA ENTITIES

Entity	Principal fields
User	name, email, password hash, role (default candidate), timestamps
Candidate	name, email, role, AI score, status (for example Shortlisted, Hired)
Job	title, company, skills, experience, location
Resume, interview, report	uploaded resume, interview record, AI evaluation report of a user

D. AI Resume Intelligence

A candidate uploads a resume in PDF format. The platform extracts the text and sends it, with an instruction to act as an expert ATS resume analyser, to a Llama 3 70B instruction model reached through the OpenRouter API [13]. The reply has the seven parts listed in Table V. The module also checks formatting, completeness and ATS compatibility, so that the candidate can correct the resume before applying, and the recruiter can read the same score.

TABLE V.
OUTPUT OF THE RESUME ANALYSIS

No.	Item
1	ATS score (out of 100)
2	Missing keywords
3	Technical skills analysis
4	Strengths
5	Weaknesses
6	Improvement suggestions
7	Recommended job roles

E. Adaptive AI Interview

The candidate chooses a company mode, a role, an experience level, an interview mode and the number of questions, and may upload a resume for personalised questions (Fig. 3). The prototype offers 14 company modes, four interview modes (technical, HR and behavioural, communication, and complete hiring) and 6, 8, 10 or 12 questions. Questions are generated from the resume, role, experience level and skills, and the difficulty is adjusted according to the previous answers. An answer is given by text or voice; the interview room shows a live transcript and the speaking pace. BERT and Sentence Transformer models [4], [6], loaded from Hugging Face [12], judge an answer by its meaning and not by its keywords. Table VI lists the aspects that are evaluated. After each session the candidate receives scores, feedback and suggestions, and the session is added to the history.

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TABLE VI.
ASPECTS EVALUATED FOR AN ANSWER

Aspect	What is judged
Technical accuracy	Correctness and depth of the content
Relevance	How well the answer addresses the question
Fluency and grammar	Clarity of the spoken or written language
Confidence	Delivery of the answer
Communication	Structure and expression across the session

F. Scoring and Recruiter Workflow

The report combines the resume score S_R and the interview score S_I into an overall score, and the overall score gives the recommendation:

$$S = round((S_R + S_I)/2), \quad result = Recommended \text{ if } S \geq 75, \text{ else } Needs\ Improvement \tag{1}$$

A company creates a job with its title, skills, experience and location, and sets the eligibility criteria, difficulty and rounds. Applicants are screened and ranked with the resume analysis, shortlisted candidates receive technical and HR assessments for the role, and the recruiter compares the resume scores, interview scores and skill-gap reports before updating the status of each candidate. Fig. 2 shows the two workflows and how they meet in the database.

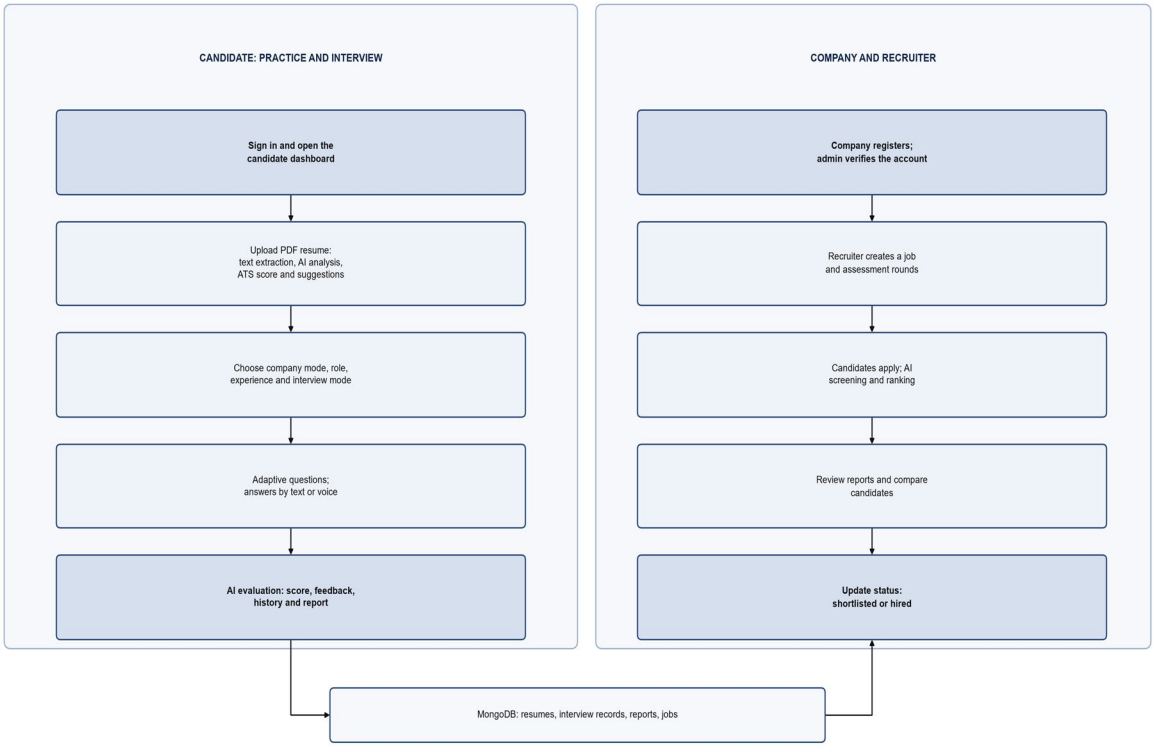


Fig. 2. Workflows of Interview IQ³: candidate practice and interview (left) and company and recruiter hiring (right) sharing one database.

VII. RESULTS AND DISCUSSION

A. Prototype Implementation

The prototype was exercised through its web interface. Fig. 3 shows the configuration of an assessment with the company modes, role and interview mode; the interview room with the AI interviewer, the candidate's video, the question with a timer, the live speech pace and the answer box; the assessment history with the number of sessions; and an executive assessment report with a competency matrix and a final verdict. Table VII lists the functions that were exercised.

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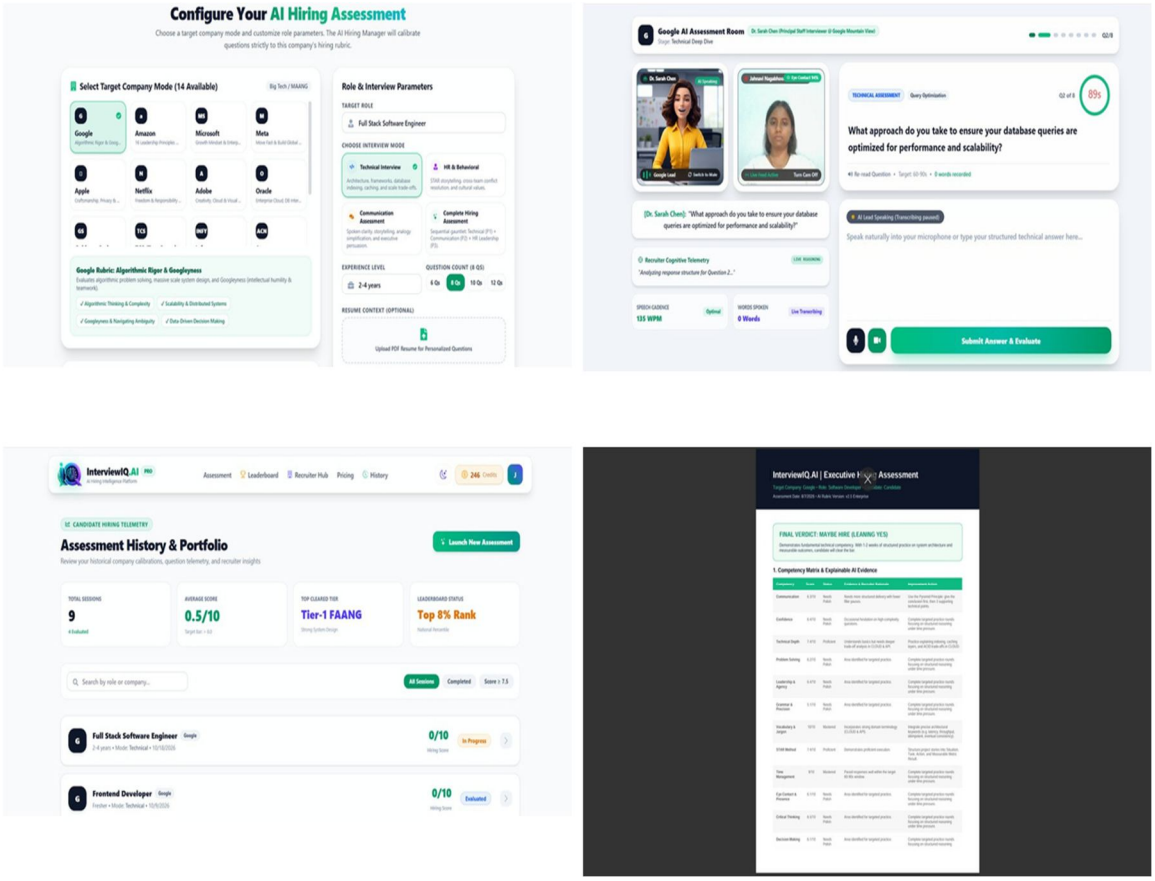


Fig. 3. Prototype screens: assessment configuration, AI interview room, assessment history and executive report.

TABLE VII.
FUNCTIONS EXERCISED ON THE PROTOTYPE

Function	Observed behaviour
Sign-in	Google sign-in with free starting credits
Assessment setup	Company mode, role, interview mode, experience level, question count and optional PDF resume
Interview room	AI interviewer, timed question, live transcript, speaking pace, text or voice answer
History	Sessions listed with role, company, date, mode and score; search and filters
Report	Competency matrix with score, evidence and improvement action; final verdict
Recruiter side	Job creation, candidate list with AI score and status, dashboard counts

B. Evaluation Plan

Because the project is at the prototype stage, a formal protocol is defined rather than reporting unmeasured figures. The agreement of the AI scores with human raters will be measured on a set of resumes and recorded interview answers that two reviewers score independently, with the Pearson correlation coefficient

$$r = \Sigma (x_i - \bar{x})(y_i - \bar{y}) / (\sqrt{\Sigma} (x_i - \bar{x})^2 \cdot \sqrt{\Sigma} (y_i - \bar{y})^2) \quad (2)$$

where x_i is the AI score and y_i the mean reviewer score of item i. The quality of the shortlist will be measured against the choice of the recruiters with

$$Precision@k = |\{ top\text{-}k\ ranked\ candidates \} \cap \{ candidates\ chosen\ by\ recruiters \}| / k \quad (3)$$

Fairness will be checked by comparing the scores of equivalent resumes in which only a personal attribute such as the name is changed. Table VIII lists the planned measurements.

TABLE VIII.
PLANNED EVALUATION METRICS

Aspect	Metric	Method
Resume score	Correlation r with reviewers	Resumes scored by two reviewers
Answer score	Correlation r with reviewers	Recorded answers scored by two reviewers
Shortlist	Precision@k	Ranking versus recruiter choice
Fairness	Score difference for equivalent resumes	Change of name or other attribute only
Latency	Time per analysis and per answer	Request to reply, including the model call
Usefulness	Score change over practice sessions	Candidate trial over several weeks

C. Discussion

The prototype shows that resume analysis, interview practice and recruiter reporting can share one account and one database, so that the evaluation a candidate practises with is the one a recruiter reads. Evaluating answers by meaning rather than by keywords, and giving the evidence and an improvement action for each score, answer the gaps of unexplained keyword screening noted in Section III.

The evaluation is limited to the prototype: the agreement of the AI scores with human raters, the effect on shortlisting and fairness are not yet measured. A language model can return different text for the same resume, so scores need validation and a fixed rubric. Resumes and answers are personal data that are sent to an external model service, which must be considered before a company adopts the platform, and the AI score is decision support that a recruiter must review and not an automatic decision.

VIII. CONCLUSION AND FUTURE SCOPE

Interview IQ³ combines AI resume analysis, adaptive interview practice and recruiter workflow management in one web platform, functions that existing tools provide separately. Role-based access, a stored history and a simple, stated rule for the overall score keep the platform understandable to both candidates and recruiters. Future work includes the quantitative evaluation described above, grounding questions and feedback in a curated question bank by retrieval-augmented generation [11], a fairness audit in the manner of [3], more capable language models for answer evaluation, integration with LinkedIn, Naukri, Indeed and company applicant tracking systems, deployment on a major cloud platform, Android and iOS applications with notifications, and predictive analytics with personalised learning roadmaps.

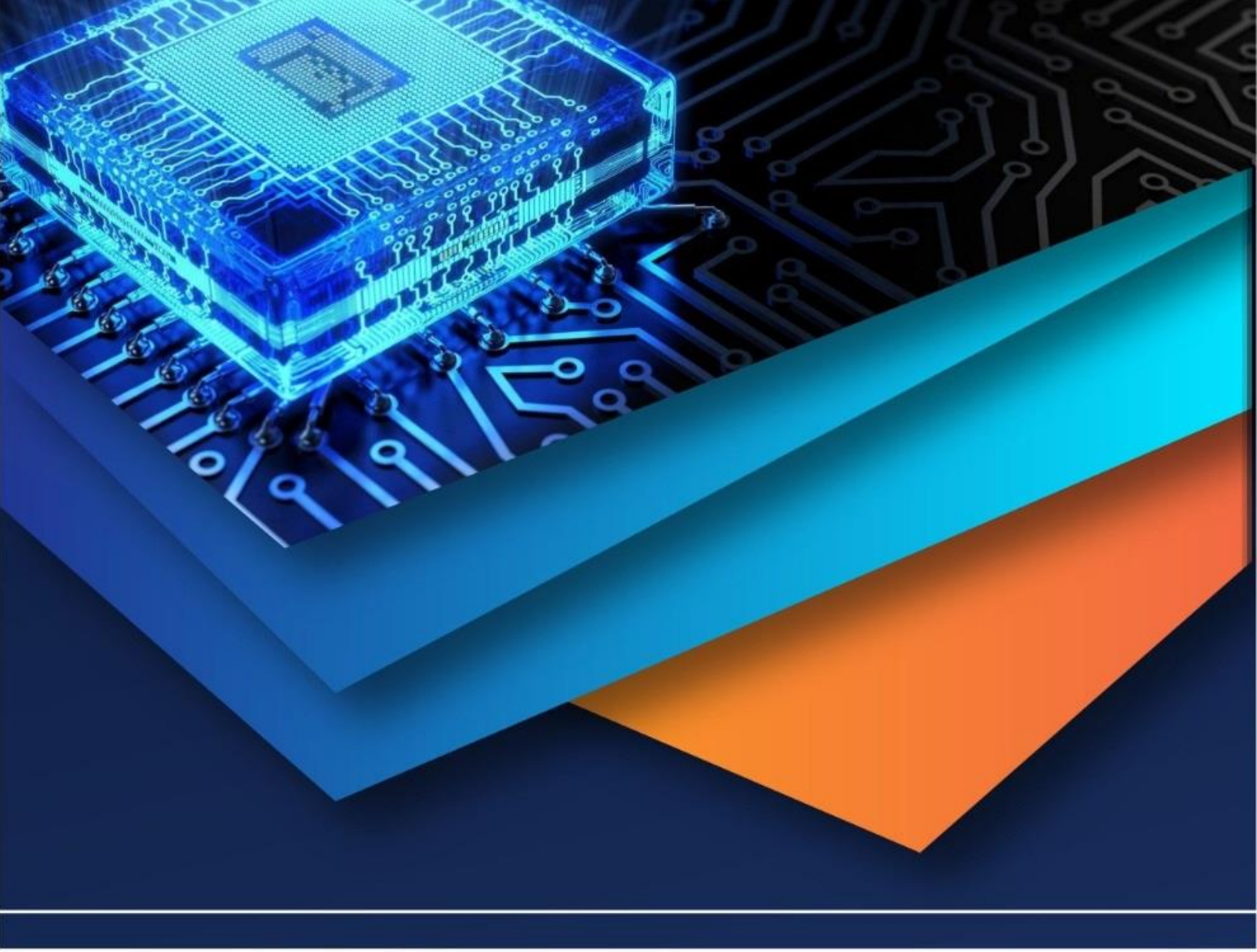
IX. ACKNOWLEDGMENT

The authors thank the Department of Computer Science and Engineering, Adhiyamaan College of Engineering, Hosur, for institutional support.

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