

# AI-Driven Interview Preparation Platform for Real-Time Feedback and Analysis

HEENA KACHHELA, SAKSHI MODAK, SAKSHI ZODE, SANIKA PAWAR, SRUSHTI BHOLE  
*Priyadarshini College of Engineering, Nagpur, India, 440016*

*Abstract- In today's cutthroat job market, nailing an interview can make or break your career dreams yet most prep methods fall short on real talk, personal touch, and honest feedback. Enter Interview Forge: an AI-driven mock interview platform that feels like the real deal. It crafts job-tailored questions using smart AI, breaks down your answers with natural language processing, and dishes out clear feedback, performance breakdowns, and tips to level up. Plus, it tracks your progress over time, turning shaky nerves into rock-solid confidence. Traditional prep like flipping through question lists or awkward peer practices often misses the mark on realism and customization, leaving candidates guessing about their weak spots. Interview Forge steps in with a web-based powerhouse blending AI, NLP, and slick tech to mimic technical, HR, behavioral, or role-specific interviews across industries. By parsing your resume, grasping job needs, generating dynamic questions, and delivering data-smart insights, it bridges the gap from book smarts to interview stardom.*

*Index Terms- Artificial Intelligence, Mock Interview System, Natural Language Processing, Interview Preparation*

## I. INTRODUCTION

In today's highly competitive job market, interview performance has become a critical determinant of career success. Employers increasingly rely on interviews not only to evaluate technical knowledge and domain expertise, but also to assess communication skills, problem solving ability, emotional intelligence, adaptability, and cultural fit. As a result, candidates who struggle to articulate their ideas clearly, structure their responses coherently, or project confidence under pressure may fail to secure offers—even when they possess strong academic qualifications and relevant experience. This makes the interview stage a high stakes barrier that many job seekers are poorly prepared to navigate.

Traditional interview preparation methods—such as reviewing static question banks, attending generic coaching classes, or participating in informal peer mock interviews—suffer from several limitations. These approaches are often generic, disconnected from the candidate's specific job role, industry, or experience level, and lack realism, scalability, and timely, structured feedback. Candidates commonly rehearse standard answers without understanding why certain responses are effective or where their own answers fall short. Without objective, formative evaluation, it becomes difficult to identify recurring weaknesses, track progress over time, or systematically refine communication, presentation, and behavioral skills. Moreover, few conventional methods support role specific practice or provide longitudinal analytics that help learners calibrate their performance against evolving hiring expectations.

Recent advances in artificial intelligence (AI) and natural language processing (NLP) have opened new possibilities for intelligent, data driven interview preparation systems. AI powered platforms can simulate realistic interview scenarios, generate role specific questions tailored to a candidate's resume and target job description, and analyze candidate responses in real time. By extracting linguistic, semantic, and structural features from spoken or written answers—such as fluency, coherence, keyword coverage, sentiment, and alignment with job requirements—such systems can provide automated, personalized feedback on clarity, completeness, relevance, confidence, and other key interview dimensions. This enables candidates to practice in an environment that closely resembles actual interview conditions, while receiving continuous, adaptive guidance that encourages reflection, self-assessment, and iterative improvement.

Furthermore, these platforms create opportunities to embed interview practice within broader learning ecosystems, such as online learning environments or career development portals, where candidates can link interview readiness with coding practice, project management skills, and domain specific knowledge. At the same time, the growing use of AI in interview preparation raises important challenges related to fairness, transparency, and ethical design—particularly in how systems handle bias in question generation, feedback, and performance evaluation. As such, the development of AI based mock interview tools represents not only a technical innovation but also a human centered opportunity to make interview preparation more accessible, personalized, and equitable for diverse job seekers..

## II. LITERATURE REVIEW

Daryanto et al. (2024) introduced Conversate, a web based LLM system that supports reflective learning in interview practice through interactive simulation and dialogic feedback. It simulates realistic interview conversations, generates follow up questions, and provides a transcript interface where users can annotate responses and discuss strengths and weaknesses with the system. This design emphasizes reflection, self aware psi, and low pressure experimentation but offers limited customization to specific job roles, industries, or resumes.

Koshti, Talekar, and Khairnar (2025) proposed an AI powered interview preparation system that integrates resume analysis with HR and technical interview simulations. The platform parses a candidate's resume to extract skills and project details, then generates tailored HR style and technical questions and evaluates responses using NLP and speech/analytics models. This tight resume-interview link enhances role specific relevance but provides only limited progress tracking and sparse performance analytics over time.

Megahed et al. (2024) presented ChatISA, a prompt engineered, multi model chatbot that includes an "Interview Mentor" module for interview preparation alongside coding, project management, and exam support activities. The mentor tailors questions to a

user provided job description and resume, demonstrating how prompt engineering can guide AI toward pedagogically useful, role adapted outputs. Yet as a general purpose assistant, ChatISA does not fully replicate staged, time bound interview flows or the role specific pressures typical of real world hiring panels.

These systems build on advances in speech and language processing (Jurafsky & Martin, 2021) and deep learning frameworks (e.g., Chollet, 2021; Brownlee, n.d.), which underpin parsing, question generation, and response evaluation in AI interview tools. Cloud based NLP services (e.g., Microsoft Azure AI Speech and Language) further ease deployment by offering pre built APIs for speech recognition, sentiment analysis, and language understanding.

Collectively, recent work highlights several trends: personalization via resume/job analysis, reflective review of transcripts, multimodal or structured feedback, and embedding interview practice within broader learning ecosystems (e.g., chatbots or cloud services). At the same time, human centered gaps persist: many systems still treat interviews as isolated question answer cycles rather than a continuous learning journey; few integrate resume based personalization, role specific simulations, structured interview flows, detailed analytics, and long term progress tracking in one cohesive experience; and there is limited empirical evidence on how these tools affect outcomes such as hiring success, self-confidence, or skill development—especially for diverse or underrepresented groups.

## III. METHODOLOGY

This study adopts a design science and iterative development approach to build and evaluate an AI based interview preparation platform. The methodology is organized into eight interrelated stages: (1) requirement analysis, (2) system design, (3) AI integration, (4) interview simulation, (5) response evaluation, (6) feedback generation, (7) UI/UX design, and (8) testing and deployment

### 3.1 Requirement analysis

We begin with a requirement analysis phase to identify user needs, desired features, and pain points in traditional interview preparation methods. This phase combines qualitative and secondary data sources:

- Semi structured interviews and focus groups with job seekers (students and early career professionals) to surface difficulties in accessing realistic practice, personalized questions, and structured feedback.
- A review of existing literature on interview preparation tools (e.g., Daryanto et al., 2024; Koshti et al., 2025; Megahed et al., 2024) to catalog common gaps such as limited role specific personalization, fragmented feedback, and weak progress tracking.
- Analysis of user journeys in conventional methods (mock interviews with peers, generic question banks, and offline coaching) to highlight issues like inconsistency, lack of immediate feedback, and low scalability.

From these inputs, we derive a set of functional requirements (e.g., resume informed question generation, role specific simulations, structured feedback, and progress dashboards) and non functional requirements (scalability, responsiveness, data privacy, and usability).

### 3.2 System design

Motivated by the requirement analysis, we design a modular, web based architecture for the platform. The system follows a client-server model with a frontend, backend, AI services, and a relational database.

- Frontend: Implemented using React (or a similar modern JavaScript framework) to support a responsive, single page application with dynamic interview sessions and real time updates.
- Backend: Built with Node.js (Express or similar) to manage user accounts, session states, resume parsing, question generation workflows, evaluation pipelines, and API orchestrations.
- Database: A relational database (e.g., PostgreSQL or MySQL) stores user profiles, resumes, job descriptions, interview logs,

question sets, evaluation scores, and feedback histories.

- AI integration layer: A lightweight orchestration layer connects the backend to external AI services (e.g., Google's Gemini API) for question generation and response analysis, while maintaining internal caches and logging for monitoring and debugging.

This architecture supports separation of concerns, scalability through cloud deployment, and extensibility for future modules (e.g., coding practice or project management simulations).

### 3.3 AI integration

The platform integrates a large language model (LLM) via the Gemini API to generate role specific interview questions that are tailored to a candidate's resume and to a given job description.

- Resume and job description ingestion: The system parses user uploaded resumes (PDF/DOC) and structured job descriptions using document processing libraries, then extracts key entities such as skills, tools, experience, projects, and responsibilities.
- Prompt engineering pipeline: A structured prompt template is designed to condition the LLM on:
  - The target role (e.g., "Backend Engineer, 2–3 years' experience"),
  - Domain and technology stack,
  - Resume derived skills and projects,
  - Question type (technical, behavioral, situational).
- Question generation: For each interview round, the backend sends a prompt to Gemini and receives a batch of role specific questions, which are then cached and optionally filtered or reordered based on difficulty, topic, or prior usage.

This approach ensures that generated questions are context aware and aligned with the candidate's profile, moving beyond generic question banks.

### 3.4 Interview simulation

We design an interactive, real time mock interview interface that simulates time bound, role based interview sessions.

- Session configuration: Users select a target role (e.g., “Frontend Developer”) and a session type (e.g., HR round, technical round), after which the system pre loads a sequence of questions from the Gemini generated pool.
- Real time interaction: The interface supports both text based and (optionally) speech based input, allowing users to type or record their answers while the system tracks elapsed time and provides visual cues (e.g., remaining time per question).
- Role based flow: The system structures the interview as a sequence of role specific rounds (e.g., resume walk through, behavioral questions, technical deep dive), mirroring common industry hiring patterns.

This simulation emphasizes continuity and pressure like conditions (e.g., time limits and sequential questions) to strengthen realism without fully replicating high stakes hiring panels.

### 3.5 Response evaluation

Answers provided by users are evaluated using NLP driven techniques to assess technical skills, communication quality, and role fit.

- Technical evaluation: For technical responses, keyword matching, code snippet analysis, and semantic similarity (e.g., against reference answers or rubrics) are used to gauge correctness, completeness, and depth.
- Communication evaluation: Linguistic features such as fluency, coherence, repetition, and clarity are extracted using token level and sentence level metrics. Sentiment and politeness indicators may be computed to assess tone and professionalism.
- Fit oriented assessment: The system compares the user’s stated experiences and skills against the job description to evaluate alignment. This may involve topic modeling or embedding based similarity (e.g., using sentence transformers) between resume/job text and the candidate’s answers.

These evaluation dimensions are combined into a multi aspect score (technical, communication, fit) that informs subsequent feedback.

### 3.6 Feedback generation

The platform generates personalized, structured feedback after each interview session.

- Automated feedback pipeline: Evaluation scores and extracted linguistic/semantic features are fed into a structured feedback template that is again processed by Gemini to produce human readable commentary. The LLM generates:
  - Strengths (e.g., “Clear explanation of your project architecture”),
  - Weaknesses (e.g., “Overuse of filler words and vague terminology”),
  - Concrete suggestions (e.g., “Practice articulating your project contributions using STAR format”).
- Reflection prompts: The system also surfaces reflection prompts (e.g., “Why did you choose this approach?” or “How could this answer better align with the role?”) to encourage metacognitive engagement.
- Long term suggestions: Feedback is tied to the user’s profile and past sessions, highlighting recurring patterns (e.g., repeated gaps in technical depth or communication structure).

This approach blends automated scoring with LLM generated narrative feedback to support both immediate adjustment and long term skill development.

### 3.7 UI/UX design

The UI/UX design focuses on usability, accessibility, and learner engagement.

- User journeys: We define core workflows (e.g., onboarding, resume upload, starting a mock interview, reviewing feedback, and tracking progress) and prototype them using low and high fidelity wireframes.
- Responsive interface: The frontend is designed to be responsive across desktop and mobile devices, ensuring consistent access to interview simulations and dashboards.
- Dashboard and analytics: A central dashboard displays:
  - Interview history (dates, roles, scores),
  - Progress over time (e.g., score trends by technical, communication, and fit),

- Topic wise strengths and weaknesses (e.g., “Databases – 70% alignment”, “System design – 45% alignment”).

Usability testing is conducted iteratively with target users to refine navigation, visual hierarchy, and feedback presentation.

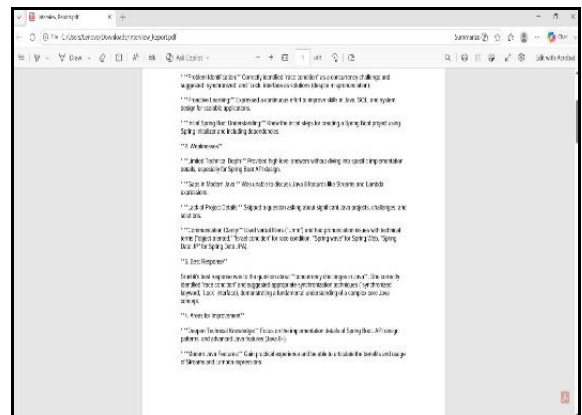
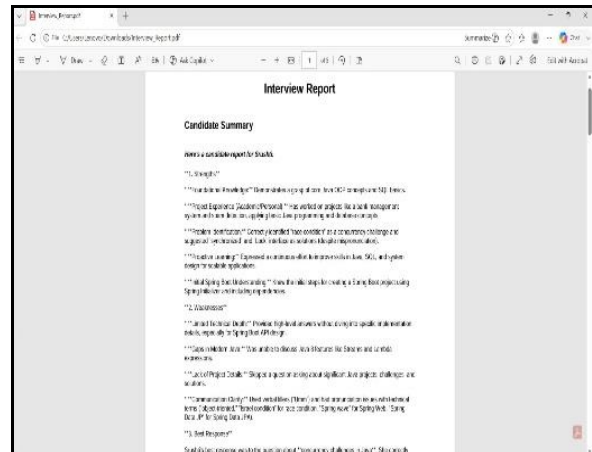
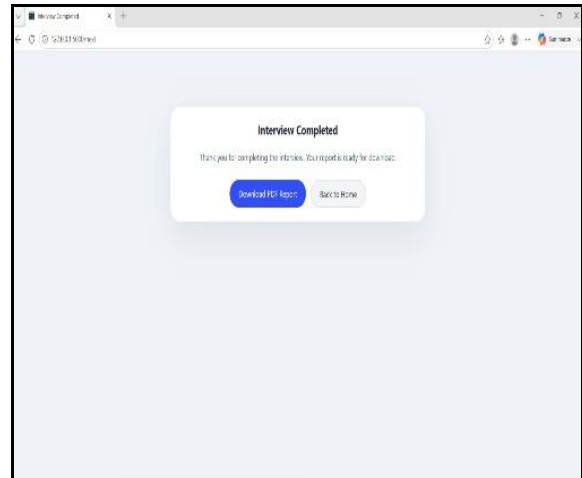
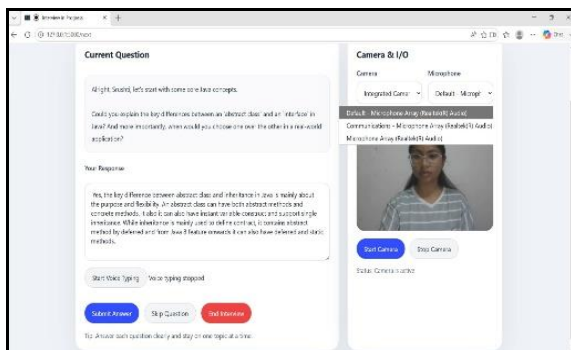
### 3.8 Testing and Deployment

Finally, the platform undergoes rigorous testing and is deployed on a cloud service for broader access.

- Functional testing: Unit and integration tests verify core components (resume parsing, question generation, score computation, feedback rendering, and session management).
- AI quality testing: A curated test set of resume job pairs and sample answers is used to evaluate question relevance, evaluation accuracy, and feedback clarity, with human reviewers rating generated outputs along multiple dimensions.
- User studies: A pilot study with a cohort of job seekers assesses usability (System Usability Scale), perceived usefulness, and learning outcomes (e.g., self-reported confidence, interview performance ratings).
- Deployment: The platform is deployed on a cloud infrastructure (e.g., AWS, Azure, or Google Cloud), with containerization (Docker) and orchestration (Kubernetes or similar) to ensure scalability, reliability, and monitoring.

This deployment enables public or controlled access, data collection for further research, and opportunities to study the long term impact of AI supported interview preparation on hiring outcomes and skill development.

## IV. OUTPUT



## V. CONCLUSION

AI-powered interview platforms are shifting preparation from rote practice to personalized, reflective learning. Systems like Conversate, Interview Ease, and others show that candidates can

become more confident and self-aware when tools combine resume-aware questions, realistic simulations, and feedback on both what they say and how they say it. Yet many challenges remain around fairness, transparency, and long-term impact, especially for diverse or underrepresented users. In short, the future of interview preparation lies in building AI tools that are not only smart, but also human-centered helping candidates grow, reflect, and walk into interviews with both skills and confidence.

#### FUTURE SCOPE

Several promising directions emerge for extending this work. First, the platform can be enhanced with multimodal analysis to incorporate speech prosody, facial expressions, and nonverbal cues (e.g., gaze, gestures) captured via webcam and microphone, enabling richer evaluation of communication style and confidence under pressure. This would align interview simulations more closely with real world hiring panels and support socio emotional as well as technical feedback.

Second, the system can be extended to support collaborative and group interview scenarios, such as team based case studies or whiteboard style coding sessions. Integrating real time multi user collaboration (e.g., shared code editors, scenario based role plays) would allow candidates to practice not only individual responses but also teamwork, leadership, and conflict resolution skills relevant to industry practice.

Third, the evaluation and feedback pipeline can be refined through longitudinal learning analytics. By tracking performance across many sessions, the platform can detect fine grained skill trajectories, personalize learning paths, and recommend targeted resources (e.g., coding exercises, communication drills, or domain specific modules). Integrating these analytics with external learning platforms (e.g., MOOCs or LMS systems) can create a broader AI supported career development ecosystem.

Fourth, the system can be evaluated in field studies with diverse and underrepresented groups to investigate fairness, accessibility, and equity. Such studies could examine how AI generated questions

and feedback adapt to different linguistic backgrounds, socio economic contexts, and neurodiverse candidates, and whether the platform reduces or amplifies existing biases in interview preparation opportunities.

Finally, the architecture can be generalized into a reusable framework or API for AI driven career readiness tools. This would allow educators and institutions to plug in custom evaluation rubrics, domain specific question banks, and organization specific hiring workflows, promoting standardization and scalability while preserving the human centered design principles demonstrated in this work.

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