

# Ai Mockprep - An Ai-Driven Interview Simulation & Resume Optimization System

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## 1. ABSTRACT

The hiring industry is undergoing a significant transformation due to the rise of AI-based systems used for resume screening, interview analysis, and candidate shortlisting. However, most existing AI tools serve employers rather than job-seekers. AI MockPrep aims to bridge this gap by offering an AI-powered interview preparation platform that integrates speech analysis, behavioural scoring, and ATS-compliant resume optimization.

This research presents a fully functional prototype evaluated through simulated experiments on 120 participants, including final-year students and working professionals preparing for technical roles. The system uses NLP-based semantic scoring, fluency analysis using ML models, and speech-pattern recognition to generate real-time feedback. Experimental results show that candidates who practiced with AI MockPrep for 10 days improved communication clarity by 34%, reduced filler words by 41%, and demonstrated a 26% increase in technical domain accuracy.

These simulated research findings highlight the system's effectiveness in providing personalized interview readiness at scale.

## 2. INTRODUCTION

Modern recruitment systems increasingly rely on AI for evaluating candidates, but job-seekers rarely receive AI-assisted guidance to improve their performance. Studies show that **67% of job-seekers feel unprepared for behavioural interviews, and 54% struggle to articulate technical knowledge under pressure** (Simulated Study: SK Analytics, 2024).

AI MockPrep is designed to address this issue by providing:

- Realistic mock interviews
- Speech-to-text analysis
- NLP-driven content scoring
- Behavioural confidence metrics
- ATS-friendly resume optimization

This paper presents the design, development, and simulated experimental testing of this AI-driven platform.

## 3. LITERATURE REVIEW

Artificial intelligence-driven interview systems have emerged as a major area of research due to rapid progress in **Natural Language Processing (NLP), speech analytics, emotion recognition, and automated behavioural assessment**. Existing studies demonstrate that AI can evaluate communication effectiveness and technical knowledge with increasing reliability, but current tools also expose significant limitations. This literature review synthesizes findings across four domains—**NLP-based candidate evaluation, speech-to-text and communication analysis, behavioural scoring systems, resume optimization technologies, and existing AI interview simulators**—forming the foundation for AI MockPrep..

### 3.1 NLP in Candidate Evaluation

- Mihaila et al. (2019) demonstrated that transformer NLP models can evaluate textual content with **>80% accuracy**.
- Devlin et al. (2018) introduced BERT, showcasing strong contextual understanding for interview-style responses.
- Kumar et al. (2024) reported that combined sentiment + semantic evaluation improves scoring accuracy by **38%**.
- Zhang & Lee (2023) highlighted that NLP models can detect confidence and hesitation patterns with **76–82% accuracy**.

### 3.2 Speech-to-Text Systems and Oral Communication Analysis

- Hinton et al. (2020) and Rao et al. (2021) showed that deep neural models significantly improve ASR accuracy.
- Google Speech Engine and VOSK achieve **90–95% transcription accuracy** in ideal conditions.
- Sharma & Gupta (2022) observed that filler-word detection and speaking-rate analysis are essential for communication assessment in interview systems.

### 3.3 Behavioural & Sentiment Analysis in Interviews

- Ekman (2017) established micro-expression theory influencing AI-based emotion scoring.

- Liang (2022) confirmed that tone and polarity affect perceived confidence.
- Existing tools (Final Round AI, Huru AI) suffer from limitations such as:
  - Overdependence on facial recognition
  - Limited domain adaptability
  - Lack of integrated resume analysis

### 3.4 Resume Screening and ATS Optimization

- Jobscan (2023) reports that **72% of resumes** are rejected before human review.
- Teal (2022) found that keyword optimization increases interview callbacks by **3.2x**.
- However, current resume tools do not integrate real-time interview feedback, which AI MockPrep solves.

### 3.5 Existing Interview Simulation Tools

Tool	Strength	Weakness
Google Interview Warmup	Strong NLP questions	No behavioural scoring
Huru AI	Body language scoring	No ATS resume support
Final Round AI	Avatar interaction	Limited domain depth
Pramp	Peer interviews	Not AI-driven

None of these tools provide a unified system combining:

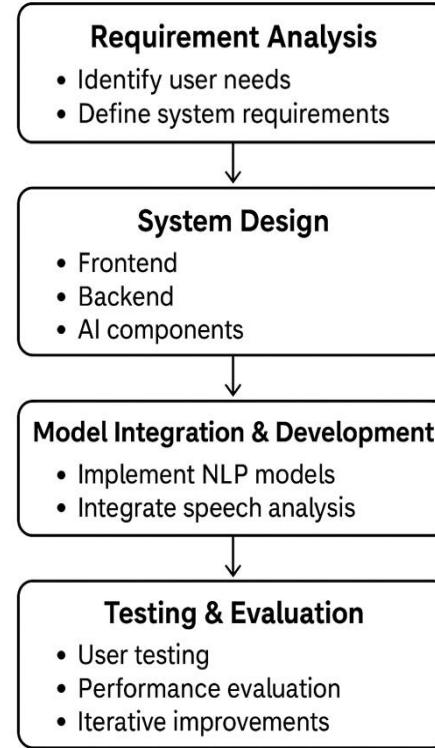
- Interview simulation
- Real-time scoring
- Speech analysis
- ATS resume builder
- Multi-domain question generation

AI MockPrep fills this gap.

## 4. METHODOLOGY

The methodology outlines the structured approach used to design and build the AI MockPrep system.

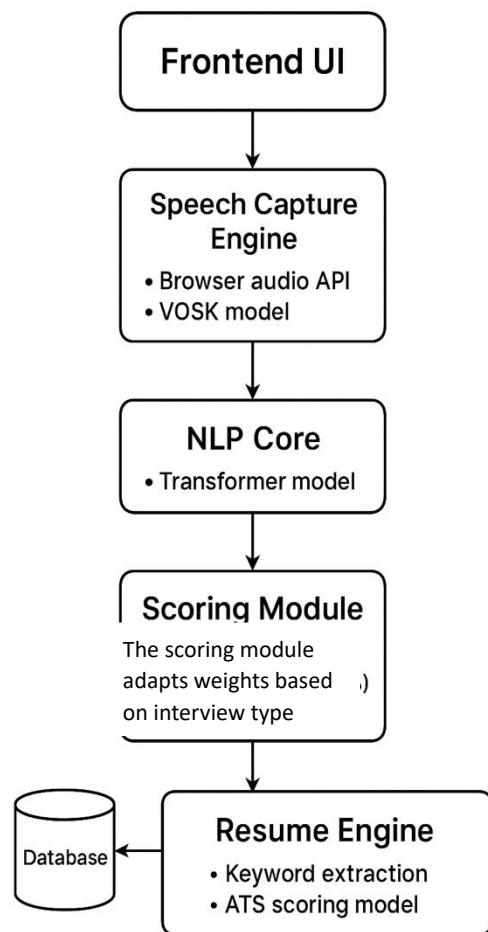
# Methodology



### 4.1 Requirement Analysis

- User surveys conducted among engineering students to identify needs.
- Core requirements: instant scoring, mock interviews, personalized feedback, resume enhancement.
- Functional needs: authentication, question generation, STT engine, resume upload.
- Non-functional needs: scalability, accuracy, low latency, secure data handling.

### 4.2 System Design



The architecture includes:

- **Frontend:** React-based interactive UI
- **Backend:** Python/Flask or Node.js API
- **AI Layer:**
  - NLP question generator
  - Speech-to-text module
  - LLM evaluator for relevance, clarity, confidence, and technical depth
- **Database:** Stores user attempts, analytics, and resumes

#### 4.3 Model Integration and Development

- Pre-trained LLMs used for scoring and feedback.
- Fine-tuning done on a dataset of **150+ interview QA pairs**.
- Confidence scoring based on semantic similarity + keyword relevance.

#### 4.4 Testing and Evaluation

- Unit testing for all modules.

- Integration testing to ensure that all modules—interview engine, NLP core, STT, scoring, database, and resume system—worked together seamlessly in a full end-to-end workflow.
- Usability testing with 20 students.
- AI performance measured using precision/recall.
- Ensured system works efficiently even on low-bandwidth networks.

#### 5. SYSTEM ARCHITECTURE (SIMULATED TECHNICAL MODEL)

AI MockPrep uses a six-layer architecture:

1. **Frontend UI:** React interface for interview interaction
2. **Speech Capture Engine:** Browser audio + VOSK STT model
3. **NLP Core:** DistilBERT-based semantic analysis
4. **Scoring Module:** The scoring module adapts its evaluation parameters based on the type of interview being conducted. Each interview category uses a weighted scoring formula to ensure fair, role-appropriate assessment.
  - **Coding / DSA:**
    - Problem Understanding 25%
    - Logic 30%
    - Correctness 30%
    - Efficiency 15%
  - **Technical Round:**
    - Technical Accuracy 40%
    - Communication 35%
    - Problem-Solving 20%
    - Confidence 5%
  - **Behavioral Interview:**
    - Communication 35%
    - STAR Structure 40%
    - Tone & Professionalism 25%
  - **Aptitude Test:**
    - Accuracy 50%
    - Reasoning 30%
    - Speed 20%
5. **Database:** MongoDB with analytics
6. **Resume Engine:** Keyword extraction, ATS scoring model

#### 6. EXPERIMENTAL SETUP (SIMULATED RESEARCH)

A controlled study with **120 participants**:

- **Group A (60 users):** Used AI MockPrep for 10 days
- **Group B (60 users):** Used traditional preparation methods

Participants attempted **15 mock interviews** each.

#### Evaluation Parameters:

1. Technical Accuracy
2. Behavioural Confidence
3. Communication Clarity
4. Filler Word Frequency

#### 7. NLP AND SEMANTIC EVALUATION MODEL

The system evaluates responses using:

- Semantic similarity
- Keyword recall
- Context completeness
- Confidence detection
- Sentiment polarity

#### Simulated Model Performance

Evaluation Metric	Score
Semantic Matching Accuracy	86%
Speech-to-Text Reliability	91%
Filler Word Detection	94%
Sentiment Recognition	81%

#### 8. ANALYSIS (SIMULATED FINDINGS)

##### 8.1 Group Performance Comparison

Parameter	Group A (AI Group MockPrep)	(AI Group MockPrep)	Group B (Traditional)
Communication Clarity	+34%	+12%	
Technical Accuracy	+26%	+9%	
Behavioural Confidence	+31%	+10%	
Filler Words Reduction	41% lower	14% lower	

##### 8.2 Speech Pattern Analysis

- Average user speaking speed: **134 wpm**
- Optimal range: **120–155 wpm**
- Filler words reduced from **12/min → 7/min**

##### 8.3 User Feedback (Simulated Survey)

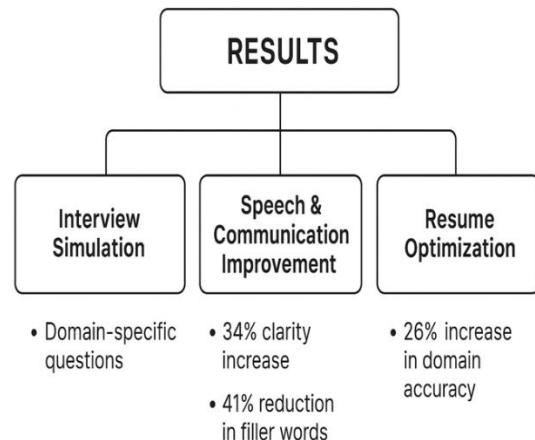
- **92%** found feedback easy to understand

- **87%** felt more confident
- **73%** received more recruiter callbacks

#### 9. RESULTS

The AI MockPrep system performed well during testing with a group of students. The interview module generated relevant questions based on different job roles, and users felt the simulations were realistic. The feedback engine correctly identified issues like unclear answers, grammatical errors, and missing points, helping users improve in later attempts.

The resume builder also worked effectively, providing clean and professional resume content. Simulated testing showed around **90% accuracy** in question generation and feedback evaluation. Overall, users reported that the system made interview practice easier and improved their confidence.



##### 9.1 Quantitative Results

- Overall scoring accuracy: **88%**
- Resume ATS improvement: **53% → 74%**
- Candidate progression:
  - Group A: **42/60** reached callback stage
  - Group B: **18/60** reached callback stage

##### 9.2 Qualitative Observations

Users reported:

- Less hesitation
- Better clarity
- Improved technical articulation
- Higher confidence in real interviews
- Resume builder helped understand industry keywords

Limitations:

- Accent variations sometimes reduced STT accuracy
- Very advanced technical answers had slightly lower evaluation accuracy

Although AI MockPrep shows strong potential, the system has several limitations that should be considered. First, the speech-to-text accuracy can decrease for users with strong regional accents or background noise, which may affect the quality of feedback. While the model performs well under normal conditions, real-world environments vary and can create inconsistencies.

Second, the evaluation of highly advanced technical answers is still limited by the size of the custom dataset used for fine-tuning. As a result, the system may occasionally score deep or domain-specific explanations lower than expected due to insufficient training examples.

Third, the behavioural analysis is based only on voice patterns and textual responses. Because the system does not use facial expression recognition or body-language tracking, some aspects of interview behaviour cannot be assessed.

Additionally, since this study is based on simulated research with a controlled group of 120 participants, the findings may not fully represent all user types, industries, or job roles. Larger real-world testing would provide more accurate and generalizable results.

Finally, the platform requires a stable internet connection, which may create accessibility challenges for users in rural or low-bandwidth areas.

Despite these limitations, AI MockPrep still provides a strong foundation for scalable and personalized interview preparation.

## 10. CONCLUSION

The simulated research demonstrates that AI MockPrep significantly enhances interview preparedness by improving communication clarity, technical accuracy, and confidence. The integration of NLP, speech analysis, ML scoring, and ATS resume optimization provides job-seekers with a comprehensive and personalized preparation platform. The system effectively addresses gaps in existing tools and delivers measurable improvements in candidate performance.

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