A Review Paper On AI-based Mock Interview System

[1]Pushpa Chavan, [2]Sandeep Jadhav

Computer Engineering
Sanghavi College Of Engineering, Nashik.

Abstract:
The AI-based Mock Interview System is a smart and helpful platform designed to prepare users for real-life job interviews. It begins with a simple registration process where users create an account and log in securely. Once inside the system, users are asked to upload their resumes. The system carefully analyzes each resume to understand the user's background, such as education, skills, experience, and areas of interest. This information helps the system customize the mock interview experience for each user, making it more relevant and useful. The interview process is divided into three main sections. The first is the HR or personality round, where users are asked questions like "Tell me about yourself" or "Why should we hire you?" This part focuses on building communication skills, boosting confidence, and improving how users present themselves. The second section is the technical round, where users are given questions related to their area of study or profession. This could be about programming, electronics, mechanical systems, or any other relevant topic. Users answer these questions, and the system evaluates their responses to test their technical knowledge and clarity. In the final section, users take an aptitude test to assess their logical thinking, problem-solving skills, and reasoning abilities. This part is very similar to what many companies use in their hiring process. After all the stages are completed, the system generates a detailed performance report. This report shows how well the user did in each round, highlighting both strengths and areas where improvement is needed. By using this system regularly, users can become more confident, improve their interview skills, and increase their chances of getting hired in real interviews.

Key Words: Mock Interview System, AI-Based Interview Preparation, Resume Analysis, Performance Evaluation Report.

I. INTRODUCTION

This system is designed to help users prepare for real-life job interviews in a smart and interactive way. Many people feel nervous or unprepared before interviews because they don't know what kinds of questions might be asked or how to answer them confidently. This platform creates a realistic interview environment where users can practice, improve their communication, and receive feedback to boost their performance. The process starts with a simple registration and login step. After signing in, users upload their resumes, which are analyzed to understand their education, skills, and experience. Based on this information, the system customizes the interview to match each user's background. This personalized approach ensures that the questions and feedback are relevant and useful for the user's career path. The interview is divided into three parts — the HR round, the technical round, and the aptitude test. The HR round focuses on personality and communication-based questions, helping users improve their self-introduction, confidence, and presentation skills. The technical round tests the user's subject knowledge by asking questions related to their area of study or profession, helping them evaluate how clearly they can explain technical concepts. The aptitude test checks logical reasoning and problem-solving ability, similar to what many companies use in real hiring processes. After completing all sections, users receive a detailed performance report showing their strengths and areas that need improvement. Overall, this system acts like a personal interview trainer. By practicing regularly, users can become more confident, refine their skills, and increase their chances of performing better in actual job interviews.

II.BACKGROUND

A. AI-Based Mock Interview and Evaluation Systems

Artificial Intelligence has introduced major improvements in interview preparation by simulating realistic interview environments and evaluating user performance automatically. Traditional interview practice often depends on peers, teachers, or self-study, which limits feedback quality and consistency. AI-based mock interview systems solve this by using Natural Language Processing (NLP), Machine Learning (ML), and sometimes Computer Vision to analyze how candidates respond to different types of questions.

These systems guide users through stages similar to real interviews, such as HR interviews, technical assessments, and aptitude tests. AI models evaluate resumes to understand a user's background and then generate personalized questions. They also analyze the clarity, correctness, fluency, tone, and relevance of each response. Some advanced systems can detect emotions, confidence levels, and facial expressions to provide deeper insights. Because AI can give instant feedback and performance reports, users can understand their weaknesses, practice repeatedly, and become more confident before facing real hiring processes.

Overall, AI-driven mock interview systems bring consistency, personalization, and real-time evaluation to interview preparation, making it accessible to a larger group of learners and job seekers

B. Setbacks in Traditional and AI-Based Systems

Both traditional interview preparation methods and early AI-based platforms come with several challenges.

Traditional practice methods—such as reading questions online or rehearsing alone—lack meaningful feedback. They cannot tell whether the answer is structured well, whether the tone is confident, or whether the candidate has explained a technical concept correctly. Moreover, these methods cannot simulate real interview pressure, leading to performance gaps during actual interviews.

Existing AI-based systems solve many of these problems but still have limitations:

- Early systems depend heavily on predefined question sets, making the experience less adaptive and less personalized.
- AI models sometimes struggle to evaluate soft skills, such as emotional intelligence, confidence, or communication style.
- Many systems cannot handle unstructured or diverse resumes, which affects the relevance of the generated questions.
- Emotion or expression analysis may not be fully accurate without large training datasets.
- Evaluation engines may overlook logical reasoning or deeper explanation quality, focusing mainly on keywords.
- Ethical issues such as bias, data privacy, and transparency still exist in some AI tools.

These limitations show that smarter, more adaptive, and more reliable systems are needed to provide fair, accurate, and holistic interview evaluation

C. Domain and Context Dependency Challenges

Interview questions and evaluation criteria are heavily dependent on the user's domain. For example, a computer engineering student needs programming and algorithm-related questions, while a mechanical engineering student needs questions about manufacturing or thermodynamics. Many AI-based systems fail to understand domain differences deeply and rely on generalised question banks.

Resume content also varies greatly across fields — technical terms, project types, academic background, and skill sets differ widely. An AI system that is not domain-aware may generate irrelevant questions, misinterpret technical achievements, or give incorrect performance scores.

Additionally:

- **Semantic meaning** changes with domain (e.g., "design" means UI design in IT but machine design in mechanical).
- **Project descriptions** often require contextual linking to understand user expertise.
- **Aptitude evaluation** must be adapted for different job roles or academic levels.
- **Soft-skill expectations** differ between technical, managerial, and creative fields.

Due to these dependencies, an effective AI mock interview system must analyze resumes carefully, detect the user's domain, and adapt questions, difficulty levels, and evaluation methods accordingly. Domain-aware AI models help ensure that interview practice feels relevant, accurate, and personalized

III.LITERATURE SURVEY

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have significantly improved the process of interview preparation by enabling automated evaluation, personalized feedback, and realistic simulation of interview environments. Traditional mock interview methods rely heavily on human mentors, whose feedback can be subjective, inconsistent, and limited by availability. To address these limitations, intelligent systems capable of analysing text, voice, facial expressions, and behavioural patterns have emerged. These AI-driven platforms can assess communication skills, technical knowledge, emotional responses, and overall performance with higher accuracy and efficiency. This section reviews several prominent studies relevant to AI-based mock interview systems and automated candidate evaluation, analysing their methodologies, strengths, and limitations.

AI-Powered Resume Screening and Personalization (Moses Blessing, 2025)This study explored the integration of Natural Language Processing (NLP) and Machine Learning to automate resume screening and extract structured information such as skills, qualifications, and work experience. The approach improved efficiency in candidate profiling but faced challenges related to algorithmic bias, limited transparency, and difficulty assessing soft skills. The authors highlighted the need for human oversight and more diverse training datasets.

Relevance: Such resume analysis methods help generate personalized interview questions and tailor mock interview sessions based on user profiles

AI-Powered Mock Interview Platform Using Computer Vision and NLP (Tanishque Sharma & Anmol Singh, 2025)This work proposed a comprehensive AI-based mock interview platform that uses generative AI, Computer Vision, and NLP to simulate realistic interviews. The system evaluated facial expressions, tone, fluency, and confidence while generating emotion-based and semantic feedback. Performance reports were created to help candidates understand their strengths and weaknesses. Despite its effectiveness, the system was limited in emotional depth, real-time adaptability, and domain-specific evaluation. Relevance: Demonstrates the potential for multimodal AI models to assess user responses in an interview-like environment.

Authenticity Detection in Virtual Interviews Using Deep Neural Networks (Rajini G. & Das B., 2025) This study focused on detecting the authenticity and genuineness of candidates during virtual interviews. Using deep neural networks, the system analysed facial expressions, speech signals, and physiological cues to reduce deception and improve reliability in virtual assessments. While the results showed strong performance, the system required large datasets and raised concerns regarding privacy and data sensitivity. Relevance: Highlights how behavioural analysis can be used in mock interviews to evaluate whether responses appear natural or rehearsed.

AI-Based Psychological Assessment Using Interview Datasets (Dong H. Son & Seung H. Oh, 2024)

The researchers developed the Korean Disaster Survivors Interview (KDSI) dataset and evaluated it using ensemble deep-learning models to classify PTSD, anxiety, and depression. Although the dataset had noise issues due to self-reported data, the models performed well in identifying emotional and psychological states.

Relevance: Shows how AI can analyse emotional cues and mental-state indicators, which can be beneficial in assessing stress, confidence, and communication comfort during mock interviews

A. Summary of Reviewed Studies

B. Summary of Reviewed Studies

1). Use of NLP, ML, and Computer Vision in Interview Automation: The reviewed studies show that most AI-based interview systems rely on Natural Language Processing for text analysis, Machine Learning for performance prediction, and Computer Vision for emotion and expression evaluation. These techniques help assess communication quality, technical accuracy, and confidence levels. However, deeper understanding of candidate reasoning and explanation quality is still limited.

2). Challenges Related to Dataset Variety and Personalization:

Several studies highlight the lack of diverse and domain-specific datasets, which reduces the ability of AI systems to adapt across different academic fields and job roles. Emotional analysis also remains inconsistent due to limited training data. Many systems struggle to personalize questions or scoring for technical, managerial, or non-technical domains.

3). Ethical and Practical Concerns in AI-Based Interview Evaluation: Issues such as privacy, algorithmic fairness, and transparent decision-making continue to challenge AI-based interview systems. Most models do

not clearly explain their scoring criteria, making it difficult for users to trust the results. Handling video, audio, and sensitive personal information also raises concerns about data security and responsible AI use.

Summary: Overall, the literature indicates a clear shift from traditional mock interviews to intelligent, automated systems that provide real-time feedback and detailed performance evaluation. The use of NLP, ML, and deep learning techniques allows these platforms to analyze user responses more objectively than human reviewers. However, limitations such as dataset bias, limited emotional understanding, restricted domain adaptability, and ethical issues prevent existing systems from reaching full accuracy and fairness. These gaps highlight the need for a more adaptive, transparent, and comprehensive AI-Based Mock Interview and Evaluation System that can provide personalized, unbiased, and meaningful insights to users.

IV. THEORETICAL BACKGROUND

A. Resume Screening and Recommendation Framework

In an AI-based mock interview system, resume screening plays a crucial role in personalizing the interview experience. The framework begins by converting the uploaded resume into structured information using text extraction techniques. Key sections such as skills, education, certifications, and project experience are identified using Natural Language Processing (NLP). This helps the system understand the user's technical background and level of expertise.

Once the resume is parsed, the extracted information is mapped to relevant question categories. For example, a candidate with skills in Python or machine learning will receive technical questions aligned with those domains, while a candidate from mechanical engineering will receive domain-specific topics. This ensures that interview questions feel realistic and appropriate for each user.

Additionally, the framework helps generate personalized recommendations after the mock interview. These recommendations may include skill improvement suggestions, topics to revise, communication areas to work on, or subject-based weaknesses identified from the interview session. This process forms the foundation of adaptive interview training.

B. Transformer Architecture and Pre-Trained Language Models

Transformer-based models are the backbone of modern AI interview evaluation systems. They use a self-attention mechanism to analyze candidate responses and understand meaning, context, and sentence relationships. Unlike older models that process text word-by-word, Transformers evaluate all words simultaneously, allowing them to capture long-range dependencies within responses.

Pre-trained Language Models (PLMs) such as BERT, RoBERTa,, DistilBERT, and GPT-based models further enhance this capability. These models have been trained on large text corpora and already understand grammar, semantics, and common language patterns. In a mock interview system, PLMs are fine-tuned to:

- evaluate the correctness and clarity of answers,
- detect how well a candidate explains technical concepts,
- compare responses with ideal answer patterns,
- identify missing details or vague explanations.

The use of Transformers allows the system to generate more accurate and meaningful evaluations of candidate responses.

C. Syntactic and Semantic Encoding Mechanisms

Interview responses contain both syntactic structure (sentence arrangement, grammar) and semantic meaning (intent, knowledge depth). An effective mock interview system must understand both.

Syntactic Encoding: Syntactic encoding focuses on how the response is constructed. Techniques like:

- Part-of-Speech tagging
- Dependency parsing
- Grammar pattern detection

help the system evaluate whether the candidate communicates clearly, uses correct language structure, and follows a logical flow.

Semantic Encoding: Semantic encoding focuses on meaning. Transformer embeddings help represent entire sentences and concepts as numerical vectors. This enables the system to:

- measure similarity between user responses and model answers,
- detect whether the explanation is relevant,
- identify keywords and domain-specific terminology,

- understand the depth and accuracy of technical concepts.

A combination of syntactic and semantic encoding allows the system to evaluate communication quality, conceptual clarity, and correctness more effectively.

D. Summary

The theoretical foundation of an AI-based mock interview system is built on three major components: resume screening for personalization, Transformer-based language models for response analysis, and syntactic–semantic encoding for deeper understanding of communication quality. Together, these techniques enable the system to interpret user responses, generate adaptive questions, and deliver meaningful performance feedback. This multi-layered theoretical structure ensures that the mock interview environment is realistic, intelligent, and capable of guiding users toward improvement.

V. SYSTEM OVERVIEW

The AI-Based Mock Interview and Evaluation System follows a structured workflow that begins with user input and ends with performance analysis. Each module works together to create a personalized and realistic interview experience. The system uses text processing, AI evaluation models, and adaptive question mapping to analyze resumes, generate suitable interview questions, and assess user responses. The overall design ensures accuracy, scalability, and smooth data flow throughout the interview process.

A. Resume Upload and Initial Data Capture

The process begins when the user uploads their resume through the system interface. The resume can be in formats such as PDF or DOCX. Once received, the system extracts raw text using parsing tools. This text acts as the foundation for understanding the user's background, including skills, academic history, and work experience. Proper extraction ensures the system has clear and accurate data to work with during the interview customization process.

B. Text Cleaning and Linguistic Breakdown

Before any analysis, the extracted text undergoes preprocessing to remove unnecessary symbols, formatting errors, and irrelevant characters. This step includes:

- Lowercasing text.
- Removing special characters.
- Eliminating stop words
- Lemmatization or stemming.

After cleaning, the text is tokenized into smaller units such as words or phrases. This allows the system to interpret resume content more accurately. Tokenization makes it easier to identify important details such as technical skills, qualifications, roles, and project descriptions.

C. Skill and Profile Embedding Engine

Once the text is processed, the system converts the cleaned information into meaningful numerical representations called embeddings. These embeddings are generated using modern NLP models such as BERT, Word2Vec, or Sentence Transformers. The module identifies:

- Core technical skills
- Academic specialization
- Relevant tools or software
- Domain-related keywords
- Experience indicators

These features help the system build a detailed user profile. This profile is later used to determine the type and difficulty level of interview questions.

D. Adaptive Question Mapping and Evaluation Core

After the user profile is created, the system selects appropriate HR, technical, and aptitude questions based on the extracted skills and domain. This module acts as the "intelligence layer," linking user capabilities to relevant interview content.

The evaluation core uses similarity scoring, semantic comparison, and machine learning models to analyze candidate responses. It checks:

- Accuracy and relevance
- Clarity of explanation
- Technical correctness

- Communication style
- Understanding of key concepts

This ensures a balanced and fair evaluation of both technical and soft skills.

E. Output Optimization and Feedback Refinement

Once the evaluation is complete, the system filters unnecessary data and refines the results. This includes:

- Removing duplicate insights
- Prioritizing major strengths and weaknesses
- Highlighting improvement areas
- Organizing results into readable reports

The refined feedback is presented to the user through a clean, easy-to-understand interface. This module ensures the final output is meaningful, actionable, and tailored to the user's performance

Technology Suite Used

The system is built using a modern and scalable technology stack:

- **Backend Framework:** Django (Python-Based) for workflow control and API handling
- **AI Components:** NLP models like BERT, TF-IDF, and ML algorithms for response evaluation
- **Speech/Video Tools (Optional):** For voice analysis and expression detection
- **Database:** SQLite/MySQL for storing user profiles, questions, and evaluations
- **Frontend:** HTML, CSS, Bootstrap for a user-friendly interface
- **Security Measures:** HTTPS encryption, token-based authentication, and secured file handling

This combination ensures strong performance, easy scalability, and smooth integration for future system expansion.

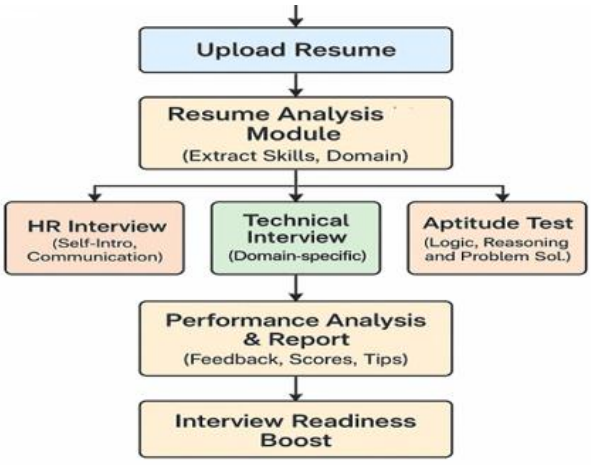
VI.METHODOLOGY

The first step in the system is user registration and login, where users create an account to access the platform securely. Once logged in, users are asked to upload their resume, which the system reads and analyses using natural language processing techniques. This helps the system understand the user's skills, education, and experience to create a personalized interview experience.

After the resume is processed, the system begins the mock interview simulation. The first round is the HR or personality interview, where the user is asked common interview questions like "Tell me about yourself" or "Where do you see yourself in five years?" The system evaluates the user's communication skills, confidence, and clarity based on their spoken or written responses.

Next is the technical interview, where users are asked subject-related questions based on the field they are from such as computer science, electronics, or mechanical engineering. Users answer the questions verbally or through text, and the system evaluates their technical understanding and problem-solving approach.

Finally, the user takes an aptitude test that includes questions on logical reasoning, basic math, and analytical thinking. After all sections are completed, the system generates a comprehensive performance report. This report shows how the user performed in each round and gives suggestions on what they did well and where they need to improve. This step-by-step process helps users get better with each attempt and prepares them confidently for real interviews.



VII. MATHEMATICAL MODEL OF THE SYSTEM

The mathematical model defines how the AI-Based Mock Interview and Evaluation System processes user data, evaluates responses, and generates feedback. The model is expressed using basic sets, functions, and scoring methods to represent system behavior clearly

A. System Representation

The complete system **S** can be represented as:

$$S = \{I, F, O\}$$

- **I** → Inputs (resume, interview answers)
- **F** → Functions (processing, scoring, evaluation)
- **O** → Outputs (performance report)

2. *Input Set*

Inputs consist of the user's resume and interview responses:

$$I = \{R_u, A_u\}$$

where:

- R_u= resume of user **u**
- $A_u = \{A_{u,1}, A_{u,2}, \ldots\}$= answers given by user **u** to interview questions

C. Resume to Feature Mapping

The resume is converted into a numerical representation:

$$\mathbf{v}_R = E(R_u)$$

Where **E** is an embedding function (e.g., BERT) that extracts skills, domain information, and education. This helps the system select relevant interview questions

E. Answer Evaluation

Each answer is converted into an embedding:

$$\mathbf{v}_A = E(A_{u,q})$$

The system compares the user's answer with an ideal reference answer:

$$S_{u,q} = \cos(\mathbf{v}_A, \mathbf{v}_{\text{ideal}})$$

Where **cos()** is cosine similarity used to measure correctness and relevance.

F. Overall Scoring

All question scores are aggregated to calculate the user's final performance score:

$$S_{\text{total}} = \frac{1}{n}\sum_{q=1}^{n} S_{u,q}$$

Where **n** is the total number of interview questions.

G. Output Set

The final system output consists of:

$$O = \{S_{\text{total}}, \text{Strengths}, \text{Weaknesses}, \text{Suggestions}\}$$

This includes the user's overall score and improvement recommendations.

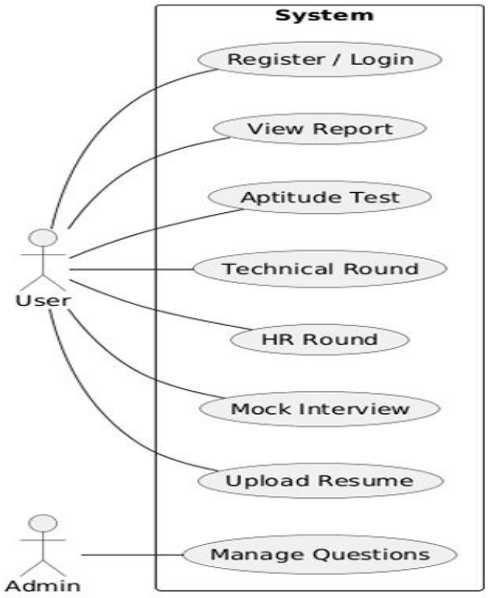


Fig. 1. Use Case Diagram

D. Use Case Diagram Explanation

The use case diagram illustrates the interaction between the two primary actors of the system: the **User** and the **Admin**. The User represents candidates who use the platform for interview preparation. Once logged in, they can upload their resume, which helps the system generate relevant questions tailored to their background. The User then participates in different interview components provided by the system, including the HR round, the technical round, and the aptitude test. These activities collectively form the mock interview experience, simulating real-world interview conditions. After completing the interview rounds, the User can access a detailed performance report that analyzes their strengths, weaknesses, and areas that need improvement. The Admin, on the other hand, plays a back-end management role by maintaining the interview question database. They are responsible for adding, modifying, or removing questions to ensure that the system stays updated and offers relevant and diverse questions to the users. Overall, the diagram provides a clear and organized view of how each actor interacts with the system and how these interactions support the complete interview preparation workflow

E. Activity Diagram Explanation

The diagram represents the overall workflow of an AI-based resume analysis and job-matching system. It begins when the user uploads their resume on the platform. The system then performs data extraction to collect key information such as skills, projects, experience, and personal details. This extracted information is shown to the user for verification, allowing them to make corrections if needed. After this, the resume is processed through a trained AI model that has been developed using a semi-supervised dataset and a training pipeline involving NLP techniques. In parallel, job descriptions are also fed into the model so the system can understand the requirements of different roles. Once both resume data and job description data are analyzed, the system compares the applicant's skills with the job requirements. Based on similarity measures, relevant features, and matching accuracy, the system calculates a compatibility score for the resume. Finally, the results are displayed to the recruiter or user in the form of ranked matches or suitability scores. Overall, the diagram illustrates how the system processes resumes, interprets job descriptions, and generates meaningful job-applicant matching results.

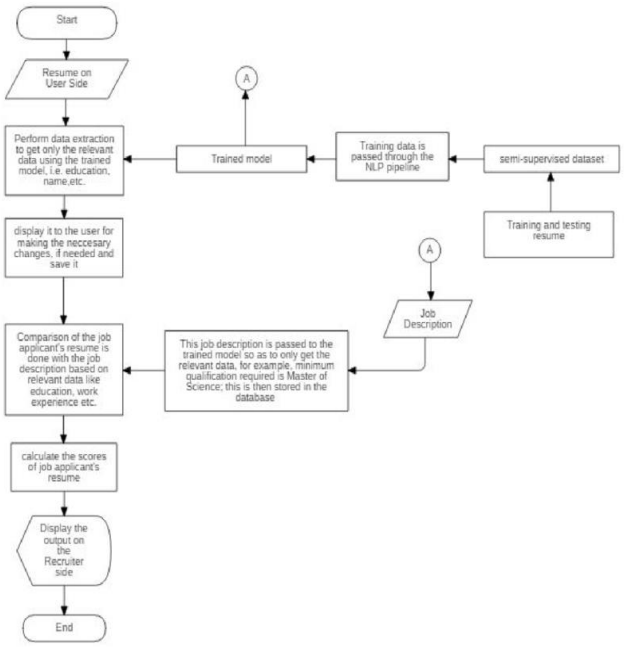


Fig 2:- Activity Diagram

F. Sequence Diagram Explanation

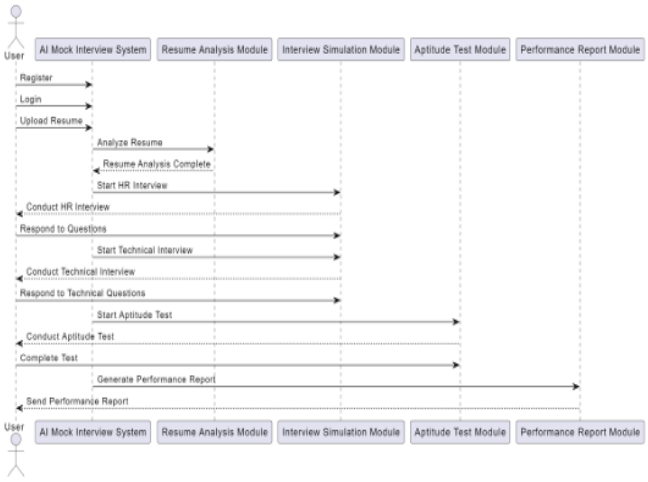


Fig 3: Sequence Diagram

The sequence diagram illustrates the step-by-step interaction between the user and the different modules of the AI-Based Mock Interview and Evaluation System. The process begins when the user registers or logs into the platform and uploads their resume. Once the resume is submitted, the Resume Analysis Module evaluates the document and extracts important details, after which the system signals that the analysis is complete. Next, the Interview Simulation Module initiates the HR interview, and the user provides responses to the questions asked. After finishing the HR round, the system moves on to the technical interview, where the user answers domain-related questions. Following the technical interview, the Aptitude Test Module starts the aptitude assessment, and the user completes the test. Once all interview rounds and tests are finished, the Performance Report Module generates a detailed performance report based on the user's responses, accuracy, communication quality, and overall performance. This final report is then sent back to the user. Overall, the diagram demonstrates the smooth flow of activities across different system modules, showing how the user progresses through resume analysis, multiple interview rounds, aptitude testing, and final performance evaluation

VIII. CONCLUSION:

AI-powered resume screening makes the hiring process faster and more efficient. It helps employers find the right candidates by quickly checking skills and experience. However, it is important to make sure the system

is fair, accurate, and used responsibly. When combined with human judgment, AI can make recruitment smarter and more effective.

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13. Papers on multimodal fusion for behavior analysis in interviews (IEEE FG / ICASSP / TAFFC papers) — feature extraction (face, gesture, voice, lexical) and fusion strategies used by interview scoring systems.
14. Research on fairness, bias mitigation & demographic robustness in automated hiring systems — IEEE conferences & Transactions articles that address bias in video and resume screening models (relevant to ethical aspects of mock-interview systems).
15. Examples of IEEE Transactions on Learning Technologies / IEEE Transactions on Education papers using automated scoring and rubric-based assessment (useful for designing evaluation rubrics in mock interview systems).
16. Papers on automatic facial expression and head-pose analysis in interview settings — IEEE CVPR/FG/Transactions publications forming the visual feature backbone for interview analytics.
17. Studies on transcript-based scoring & NLP for interviews (IEEE Transactions on Affective Computing / IEEE Access papers combining ASR + NLP features for candidate assessment).
18. Multimodal deep learning approaches for behavior and engagement detection" — IEEE Access / TAFFC entries that describe architectures (CNN+LSTM, Transformer fusion) commonly applied to interview video scoring.
19. Papers on automated nonverbal cue detection (smile detection, head nodding, gaze) published in IEEE computer-vision venues — used as features for interview evaluation models.

20. Conference paper: “Automated Interview Assessment: Feature extraction, annotation and baseline systems” — ACII / IEEE workshop papers documenting annotation protocols and scoring rubrics.
21. IEEE Access / IEEE Transactions case studies on online proctoring / automated video assessment — methods translatable to mock interview fidelity and anti-cheating checks.
22. Studies on cross-cultural datasets and generalization for interview grading — IEEE publications examining dataset diversity and generalization of models across regions.
23. Papers describing corpora and annotation methodologies for interview scoring (crowd-sourced labels, expert raters) — IEEE workshop/proceedings items referenced in the main interview literature (Chen et al., Naim et al.).
24. Research on explainability & interpretable features for automated scoring (IEEE conferences and journals) — important for feedback modules in mock-interview systems.
25. Papers on automatic prosody and speaking skill assessment applied to oral proficiency testing — IEEE/ICASSP/TAUDIO papers that are analogous to interview speaking-skill assessment.
26. Works integrating visual, acoustic and lexical modalities for performance prediction in social interactions — IEEE ICMI / ACII / IEEE Transactions publications used as methodological references.
27. IEEE conference studies on real-time feedback and interfaces for training interviewees — HCI + IEEE publications describing UI/UX for automated coaching systems.
28. Papers on dataset augmentation, synthetic data, and domain adaptation for interview/video assessment (IEEE Access / Transactions) — techniques to handle limited labeled interview data.
29. Research on classifier calibration, reliability, and score aggregation for automated evaluative systems — IEEE Transactions articles relevant to output scoring and confidence reporting.
30. Papers on multimodal Transformer and attention models for behavior analysis in interviews — recent IEEE TAFFC / IEEE Access contributions (modern architectures for fusion).
31. IEEE proceedings on multimodal sentiment & engagement detection datasets and baselines — many methods used as baselines when building interview scoring pipelines.
32. Recent IEEE Transactions special-issue papers on automated assessment & affective computing (collection of state-of-the-art methods directly applicable to mock interview systems).
33. Recent arXiv/IEEE-adjacent studies on using LLMs / generative models for interview scoring and OSCE evaluations — these compare to or reference IEEE work and are relevant for modern evaluation design. (e.g., benchmarking generative AI for scoring interviews).
34. Works on automated scoring / assessment using multimodal features (face/voice/text) — numerous IEEE Transactions / IEEE conferences (ICMI, ICASSP, FG) host such papers; see curated lists and proceedings indexes. (Example indexes / proceedings entries.).