



## A Review on Adaptive Interview Preparation System

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### Abstract:

Traditional interview preparation methods often lack personalization and fail to provide dynamic, real-time response for effective skill development. This paper reviews the basic technologies required to develop an adaptive interview prep bot, which is a versatile platform designed to simulate realistic interview scenarios. The proposed system integrates several major AI-operated modules: a re-introduction to generate sewn questions, an adaptive engine for dynamic text-based Q and A, an integrated growth environment with an autograph for real-time code evaluation, an integrated growth environments, and the basic feeling to detect the basic feeling to offer feedback on soft skills. By synthesizing research from areas of natural language processing (NLP), affectionate computing, and automated code analysis, this review underscores a harmonious outline for creating an intelligent, end-to-end interview practice tool. The resulting platform aims to provide candidates with a strong, accessible and personal solution to significantly increase their interview readiness.

**Keywords:** component, formatting, style, styling, insert

## 1. INTRODUCTION

In today's competitive job market, how well a candidate prepares often determines their chances of success. Traditional methods of interview preparation, while sometimes useful, are typically time-consuming and fail to expose candidates to the full range of questions or real-life interview situations they might face. These conventional approaches also struggle to adapt to different job roles, require considerable effort from both candidates and recruiters, and rarely replicate the pressure or flow of an actual interview. As a result, many candidates miss opportunities to develop strong communication and professional skills. To address these challenges, this paper reviews the concept of an **AI-driven Adaptive Interview Preparation Bot** a system designed to offer a realistic, multi-stage interview experience that includes resume screening, HR evaluation, and technical testing.

To overcome these limitations, this paper reviews the concept of an AI-based Adaptive Interview Preparation Bot. The aim of such a system is to bridge the shortcomings of traditional interview practice by creating an immersive, realistic, and multi-stage interview experience that covers resume screening, HR evaluation, and technical assessment.

The foundation of this system lies in combining advanced artificial intelligence techniques such as **natural language processing (NLP)** for resume analysis and question generation, an **HR simulation module** that uses emotion detection and speech recognition to evaluate behavioral responses, and a **technical assessment module** that measures domain-specific expertise[1]. This review discusses the underlying research and technologies supporting these components. By integrating studies on automated resume evaluation, emotion and speech analysis, and adaptive questioning, the paper presents a framework for developing an intelligent and personalized platform[1] that effectively replicates the dynamics of real-world interviews.

## 2. METHODOLOGY

The proposed adaptive interview PrepBOT integrates multiple AI techniques into a consolidated platform[1]. The system architecture is built on a flask backend that manages core processing modules, reaction-based frontal and websocket connections for user interface to ensure seamless, low-latency communication between the client and the

server. A -re-analyzed and applicant tracking system (ATS) module This module is designed to analyze and evaluate the user's resume to produce and respond related interview questions. The process contains several stages:

**Data Extraction and Parsing:** The system uses a combination of scanned documents and ICAL optical character Recognition (OCR) for scanned documents and natural language processing (NLP), such as PDF and term analyzed to different resume formats in structured, analysis data.

**Entity Recognition:** Named Entity Recognition (NER) is working for identifying key information such as technical skills, project details and qualifications and Ka RCT.

**Scoring the quality and consistency of content:**

Transformer based NLP models such as Bert are used to evaluate grammatical purity and formatting. Readability is more measured using metrics such as flash-kinoid scores.

This frequency-opposite document frequency (TF-IDF) algorithm is used for important keywords ka Rectic, which is then compared to a compatibility score and comparing job descriptions using Kosin equality and latent semantic analysis (LSA).

**Feedback Generation:** The module produces a feedback report that highlights the missing skills, suggests structural adjustments, and recommends related keywords to be optimizing resumes for both ATS consistency and recruitment.

**B. Feeling search module** To respond to non-verbal signals, the system includes a real-time emotion search module that analyzes the user's facial manifestations during interview simulation.

**System Architecture:** Video streams are captured on priority using WeberTC (Web Real-Time Communication) and transmitted to the flask backend via socket connections. The backend processes the video frames and removes the results of the spirit analysis for live visualization, ensuring interactive user experience with minimal delay.

**CNN Processing Pipeline:**

**Input and Preprocessing:** Video frames are captured, sized and normalized for continuous input. The defeat of the face -to -face algorithm identifies the facial area juice (ROI) of the algorithm algorithm.

**Symptom Extraction:** Its strong image classification is used for the Conventional Neural Network (CNN) for capabilities. The initial conventional layers find basic features such as edges, while ER -layers identify complex patterns correspond- ing to muscle movements. The pooling layers reduce the spatial parameters while maintaining the main information.

**Emotion Classification:** features pass through fully connected layers, and the softmax activation function produces the distribution of probability in seven emotional conditions: happiness, sadness, anger, fear, surprise, dislike and neutral. The model cited in the study was trained on the FER-2013 dataset, and achieved high accuracy.

**C. Evaluation of speech recognition and response** This module gains and analyzes the user's spoken answers for both technical accuracy and behavioral insights. **Speech-to-text conversion:** Priority uses a library such as reaction recognition

by capturing a user's voice and writing it in the text in real- time. This text is constantly sent to the flask backend via a website connection.

**Linguistic and behavioral analysis:**

Backed uses NLP methods to analyze the text transcript for local consistency, spirit and complexity.

The characteristics of speech such as peach and tempo are also analyzed to estimate the user's confidence or levels of anxiety.

**Technical Answer Evaluation:** For technical questions, the system gives the benefit of the model Fine-Tune Bert (bilateral encoder representations from transformers). The candidate's response and reference answer is converted into semantic vector embeddings. The Cosine similarity metric is then used to certify the semantic similarity between the two vectors to determine the purity of the candidate's response.

**D Dashboard and Response System** The final component is a unified dashboard that integrates the analysis of all modules to provide a comprehensive display report. The feedback module merges the results of ATS analysis, HR assessment (spirit and speech analysis) and technical evaluation. This integrated report highlights their power and fields for users to improve their power and their resume, technical knowledge and improve communication skills.

### **AUTOMATED RESUME ANALYSIS**

**Resume Analysis Module** The Resume Analysis Module automates the screening of resumes to overcome the inefficiencies and biases of manual review. It intelligently parses unstructured resumes and ranks them against job descriptions using Natural Language Processing (NLP) and machine learning[2]. The process is typically divided into two phases:

1. **Information Extraction:** This phase converts raw resume text into a structured format.
2. **Text Preprocessing:** Extracts text from files (.pdf, .docx) and cleans it by removing stopwords and special characters.  
**NLP Techniques:** Employs tokenization (splitting text into words), stemming/lemmatization (reducing words to their root form), and Part-of-Speech (POS) tagging to understand grammatical context.
3. **Named Entity Recognition (NER):** Identifies and classifies key data into categories like skills, education, experience, and contact information, often outputting a JSON summary[3].
4. **Candidate Ranking:** This phase scores and ranks the processed resumes based on their relevance to a job description. **Vector Space Model (VSM) with Cosine Similarity:** Resumes and job descriptions are converted into numerical vectors using methods like TF-IDF. Cosine similarity then measures the likeness between the documents to calculate ranking
5. **Latent Dirichlet Allocation (LDA):** This modeling approach identifies underlying themes (e.g., "Software Engineering") in resumes. It assigns topic probabilities to entities like skills and experience to generate a content-driven rating for each candidate[2][3].

**ADAPTIVE QA MODULE**  
This module generates personalized interview questions by combining data from the candidate's resume with a specified difficulty level, simulating a dynamic, semi-structured interview. It aims to move beyond static questions to provide a richer, more conversational experience[4].

#### **Methodology**

**Resume-Driven Topics:** Structured data extracted from the resume (e.g., skills, work experience) serves as a "topic guide" for the AI interviewer.[4]

**Adaptive Probing:** The system employs an AI "Probing Agent" that formulates follow-up questions to achieve both breadth and depth in the conversation. It starts with broad, open-ended questions and adjusts its questioning based on the interviewee's responses[4].

**Question Difficulty Levels** Level 1: Easy (Factual Recall)

Asks candidates to describe information directly from their resume.

Example: "Your resume lists the project '[Project Name]'. Can you give me an overview of what it was about?"

Level 2: Medium (Application and Connection)

Requires candidates to connect skills to specific experiences, probing for deeper understanding.

Example: "How did you apply the [Skill] you listed in your project at [Company Name]?"

Level 3: Hard (Behavioral and Scenario-Based)

Uses behavioral and hypothetical questions to test problem-solving and understand the "why" behind a candidate's actions.

[4][6]Example: "Describe a time you faced a major setback in '[Project Name]' and how you resolved it."

**Adaptive Mechanism** The system adjusts the difficulty of subsequent questions based on the candidate's performance. If a candidate answers a difficult question well, it may ask another. If they struggle, it can revert to an easier question on the same topic to build confidence before proceeding, gently steering the conversation as an effective interviewer would[5].

### CODE EDITOR MODULE

This module provides real-time, automated feedback on programming exercises by comparing a user's code against a single reference implementation, rather than an extensive test suite. It uses a "differential semantic analysis" approach to find meaningful logical errors instead of just counting passed tests.

**Methodology** The system, based on the AUTOGRADER tool, follows a semantics-based workflow:

**Initial Check:** An input is generated, and the outputs of the user's submission and the reference code are compared. A mismatch immediately flags the code as incorrect.

**Path Deviation Search:** If outputs are identical, the tool analyzes the execution traces using symbolic execution and weakest preconditions to create mathematical formulas ( $F_s$  and  $F_r$ ) representing each path's logic. It then searches for an input that satisfies the conditions for one path but not the other, represented by the formula  $(F_s \rightarrow F_r) \wedge (\neg F_s \wedge F_r)$ [7].

A solution to this formula is a potential counterexample that reveals a path deviation.

This formula is used to find an input  $x$  that causes the execution paths of the submission ( $F_s$ ) and the reference ( $F_r$ ) to deviate. If this is unsolvable, the deviation is ignored[7].

#### Feedback and Advantages

**Feedback:** Instead of a list of failed tests, the system provides a specific counterexample (a concrete input) that triggers the identified path deviation, making it easier for users to debug[7].

**Accuracy:** This method is more robust than test suites. In an evaluation, it found no false negatives (incorrect code marked as correct) and identified 11 errors in an online judge's test-based grading[7].

**Efficiency:** It reduces instructor workload by requiring only a single correct reference implementation, not a comprehensive set of test cases[7].

### SOFT SKILLS BASED INTERVIEW MODULE

This module provides a platform for users to practice and receive feedback on their soft skills through a simulated, dynamic interview. It leverages AI Conversational Interviewing, where a Large Language Model (LLM) acts as an adaptive interviewer, moving beyond the rigid format of structured surveys to engage candidates in an open-ended dialogue. This approach allows for a more nuanced assessment of interpersonal and communication abilities.

**Methodology** The module functions by first capturing and transcribing the user's spoken answers and then evaluating them against key soft skill metrics.

1. **Speech Recognition and Transcription** When a user responds verbally, their speech signals are processed through a sophisticated pipeline to convert them into text[8].

**Signal Processing:** The system captures the user's voice, creating a digital signal. This signal is then filtered to remove background noise and normalized to a constant volume level[8]. **Phonetic and Word Recognition:** The cleaned signal is broken down into small segments, which are matched to phonemes (the basic units of sound) using acoustic models. These phonemes are then assembled into words using a lexicon (dictionary)[8].

**Text Generation:** Finally, grammar rules and language modeling are applied to arrange the recognized words into coherent sentences, generating the final text transcription.

2. **Evaluation and Feedback** Once transcribed, the user's responses are assessed using a combination of quantitative and qualitative metrics similar to those used in research studies to evaluate interview performance[8].

**Quantitative Metrics** These are objective, computational measures of the user's response patterns:

**Response Length:** Calculated as the number of tokens (words) per answer, this metric provides a granular measure of information density.

**Readability:** Scores like the Flesch Reading Ease are computed on the transcribed text to evaluate linguistic complexity[8].  
**Qualitative Soft Skill Assessment** The system evaluates the substance of the user's answers against key communication competencies. These assessments can be automated or, in a training context, rated by human coaches based on the transcript[9]. Key assessed criteria include:

**Clarity:** How easy the response is to understand.

**Engagement:** The level of enthusiasm or interest shown in the response.

**Specificity:** The amount of detailed information provided.

**Relevance:** How directly the response addresses the question asked.

**Tone:** The appropriateness of the tone used for a professional context.

This dual approach[9] provides users with comprehensive feedback, helping them understand both the structure and the qualitative impact of their verbal communication[9].

## II. OBJECTIVES

The primary objective of this review paper is to conduct a comprehensive survey and synthesis of the state-of-the-art artificial intelligence technologies required to develop an Adaptive Interview Prep Bot. This review will examine foundational research across several key domains to establish a cohesive technical blueprint for an intelligent interview simulation platform.

The specific aims are:

**To review Natural Language Processing (NLP) techniques:** for automated resume analysis, including methods for entity recognition, topic modeling, and relevance scoring that enable personalized question generation[2][3].

**To investigate the application of Conversational AI and Large Language Models (LLMs)** in creating adaptive, semi-structured dialogues for both technical and behavioral assessments, with a focus on context-aware probing questions[4][5].

**To analyze Automated Program Analysis** methods for robust code evaluation, particularly the shift from traditional test-case-based grading to formal semantics-based approaches like symbolic execution for identifying path deviations and generating actionable counterexamples[7].

**To explore Speech Recognition and Linguistic Analysis** for capturing and evaluating spoken responses in soft skills interviews, assessing key metrics such as clarity, relevance, and tone[8][9].

By integrating insights from these fields, this paper seeks to provide a framework for designing and implementing an end-to-end platform that offers a more effective and personalized alternative to traditional interview preparation methods.

## 3.RESULT AND OUTCOME

Based on the literature reviewed, the empirical results from various studies demonstrate the effectiveness and viability of each module proposed for the Adaptive Interview Prep Bot. This section synthesizes the key findings and outcomes, highlighting the performance of AI-driven techniques in resume analysis, conversational interviewing, and code evaluation.

### Performance of Automated Resume Analysis

Research into automated resume rating systems shows strong quantitative results. A model utilizing Latent Dirichlet Allocation (LDA) and SpaCy's Named Entity Recognition (NER)[2] achieved an overall accuracy of 82% in rating resumes based on attributes like skills, experience, and education. When focusing solely on skills, the accuracy was

77%, demonstrating a robust capability for content-driven evaluation rather than simple keyword matching. The NER component proved effective at identifying specific entities, with "Skills" achieving an F1-score of 0.761. The outcome is a system that can reliably extract a candidate's key qualifications to enable a personalized, data-driven initial screening and subsequent interview customization.

#### Efficacy of AI-Led Conversational Interviews

Studies comparing AI-conducted interviews to human-led interviews reveal that AI can serve as an effective substitute, resolving the traditional trade-off between depth and scale[8][9]. The key outcomes include:

**Comparable Data Quality:** AI conversational interviewing can produce data of a quality comparable to that of human-led interviews. When participant responses were assessed by human coders, there were no substantial differences between the AI and human conditions on metrics like clarity, relevance, specificity, and tone. Notably, AI-led interviews elicited significantly longer responses on average (52.39 words vs. 32.81 for humans).

**High User Satisfaction and Preference:** It is technically feasible to conduct in-depth interviews at scale with high user engagement. In a large-scale study, 82% of respondents reported a positive overall experience, and 73.7% found the AI conversation to feel natural. Remarkably, a majority of participants (53.2%) stated a strict preference for the AI interviewer over a human one.

**Superior Data Richness:** The adaptive, probing nature of AI interviews uncovers far richer insights than single, open-ended questions. An analysis showed that a full interview yielded an average of 5.9 assigned codes[5]

#### Accuracy of Semantics-Based Code Evaluation

For the automated assessment of coding assignments, a semantics-based approach has shown superior results compared to traditional test-case methods. The AUTOGRADER tool[7], which compares a student's submission against a single reference implementation, yielded the following critical outcomes:

**High Accuracy and Soundness:** The system achieved an extended accuracy of 98.62% on a large dataset of student submissions. Most importantly, the evaluation found no false negatives, meaning no incorrect program was graded as correct. This soundness is a crucial advantage over test-based systems.

Paper Title	Author	Key Focus Area	Summary of Key Findings
Do large language models resemble humans in language use?	Cai, Z. G., Duan, X., Haslett, D. A., Wang, S., & Pickering, M. J.	Comparing LLM (ChatGPT, Vicuna) language use to human patterns across 12 psycholinguistic experiments.	<ul style="list-style-type: none"> <li>• ChatGPT showed human-like responses in 10 out of 12 experiments, while Vicuna did so in 7 out of 12 .</li> <li>• Both models successfully replicated human behaviors such as sound-shape/gender associations, word-meaning priming, structural priming, and interlocutor sensitivity .</li> </ul>
AI Conversational Interviewing:	Wuttke, A., Aßenmacher, M., Klamm, C., Lang, M.	Using Large Language Models (LLMs) as	<ul style="list-style-type: none"> <li>• AI interviewers can produce data quality</li> </ul>

<p>Transforming Surveys with LLMs as Adaptive Interviewers</p>	<p>M., Würschinger, Q., &amp; Kreuter, F.</p>	<p>adaptive interviewers to conduct scalable, in-depth conversational surveys.</p>	<p>comparable to traditional human-led methods, demonstrating the general viability of the approach .</p> <ul style="list-style-type: none"> <li>• AI interviewers made different types of errors than human interviewers: the AI predominantly failed to ask follow-up questions (88% of violations), while humans often failed at active listening (94% of violations).</li> </ul>
<p>Automatic Grading of Programming Assignments: An Approach Based on Formal Semantics</p>	<p>Liu, X., Wang, S., Wang, P., &amp; Wu, D.</p>	<p>A tool called AUTOGRADER that automatically determines the correctness of programming assignments using a single reference implementation.</p>	<ul style="list-style-type: none"> <li>• The system uses "differential semantic analysis" to find semantically different execution paths between a student's submission and the reference code .</li> <li>• It achieved an overall accuracy of 92.80%, which increased to 98.62% when timeouts were classified as correct .</li> </ul>
<p>Conducting Qualitative Interviews with AI</p>	<p>Chopra, F., &amp; Haaland, I.</p>	<p>An AI-assisted method for conducting large-scale, semi-structured qualitative interviews to bridge the gap between qualitative and quantitative research.</p>	<ul style="list-style-type: none"> <li>• High respondent satisfaction and engagement were observed; 82% rated the experience positively, and 53.2% stated a strict preference for an AI over a human interviewer .</li> <li>• The AI interviewer architecture consists of specialized agents (Security, History, Probing, and Topic) to manage the conversation</li> </ul>

			flow, ensure security, and maintain context .
QoE Estimation of WebRTC-based Audio-visual Conversations from Facial and Speech Features	Bingol, G., Porcu, S., Floris, A., & Atzori, L.	Estimating the Quality of Experience (QoE) for video calls by analyzing users' facial expressions and vocal speech characteristics.	<ul style="list-style-type: none"> <li>Combining facial and speech features using a data fusion technique significantly improves QoE estimation accuracy .</li> <li>A model trained on both facial and speech data achieved a mean accuracy of 0.93, outperforming models trained on only facial features (0.78) or only speech features (0.86) .</li> </ul>
Resume Evaluation through Latent Dirichlet Allocation and Natural Language Processing for Effective Candidate Selection	Jagwani, V., Meghani, S., Dhage, S., & Pai, K.	A system for rating resumes using Latent Dirichlet Allocation (LDA) for topic modeling and SpaCy's Named Entity Recognition (NER) for entity extraction.	<ul style="list-style-type: none"> <li>The proposed model achieved an overall accuracy of 82% in its evaluation .</li> <li>The system first uses SpaCy's NER to extract key entities like college name, degree, work experience, and skills .</li> <li>LDA is then used to identify latent topics and assign topic probabilities to the extracted entities.</li> </ul>
Virtual Interviewers, Real Results: Exploring AI-Driven Mock Technical Interviews on Student Readiness and Confidence	Gomez, N., Batham, S. S., Volonte, M., & Do, T. D.	A formative study exploring whether a multimodal AI system can realistically simulate mock technical interviews to improve student confidence and readiness.	<ul style="list-style-type: none"> <li>Participants found the AI mock interview to be realistic and helpful, with 80% finding the AI's speech and conversational style to be natural .</li> <li>The system was perceived as a confidence-boosting tool by providing a low-stakes, judgment-</li> </ul>

			free environment that reduced anxiety .
SPEECH RECOGNITION SYSTEMS - A COMPREHENSIVE STUDY OF CONCEPTS AND MECHANISM	Jain, N., & Rastogi, S.	A comprehensive review of the concepts, mechanism, and challenges of speech recognition systems.	<ul style="list-style-type: none"> <li>The core mechanism of speech recognition involves Signal Processing (filtering noise), Phonetic and Word Recognition (matching sounds to phonemes and words using acoustic models and a lexicon), and Task Recognition (assembling words into text using grammar) .</li> </ul>
AN AUTOMATED RESUME SCREENING SYSTEM USING NATURAL LANGUAGE PROCESSING AND SIMILARITY	Daryani, C., Chhabra, G. S., Patel, H., Chhabra, I. K., & Patel, R.	An automated resume screening system that uses NLP and similarity measures to rank candidates based on a job description.	<ul style="list-style-type: none"> <li>The system operates in two phases: Phase 1 (Information Retrieval) uses NLP techniques like tokenization and Named Entity Recognition (NER) to parse resumes and create a summarized JSON output .</li> <li>Phase 2 (Candidate Recommendation) uses a Vector Space Model, assigning weights to terms with TF-IDF, and then calculates the Cosine Similarity between resume vectors and the job description vector to rank candidates.</li> </ul>

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