

An AI-Based Virtual Interview Assistant for Adaptive Interview Simulation and Feedback using NLP

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Abstract—Interview preparation plays a vital role in determining a candidate's employability; however, access to personalized and scalable interview practice remains a significant challenge for many students and job seekers. Conventional preparation methods such as manual mock interviews, coaching sessions, and static question banks are either resource-intensive or insufficiently adaptive to individual candidate profiles. As a result, many candidates face difficulty in articulating their knowledge and experience effectively during real interviews. This paper presents a Virtual Interview Assistant designed to simulate personalized interview experiences using resume-based question generation and automated feedback mechanisms. The proposed system accepts a candidate's resume as input and extracts relevant information such as skills, education, work experience, and projects using natural language processing techniques aligned with Applicant Tracking System (ATS) standards. Based on this extracted information, the system dynamically generates technical and human resource interview questions tailored to the candidate's background. During the virtual interview session, candidates respond to questions through voice-based interaction. The system evaluates these responses using language understanding techniques to assess relevance, clarity, and conceptual correctness. Structured feedback is then provided to highlight strengths, identify gaps, and suggest areas for improvement. By integrating resume analysis, adaptive question generation, interview simulation, and feedback evaluation into a unified framework, the Virtual Interview Assistant aims to deliver a realistic and scalable interview preparation environment. The proposed framework is application-oriented and product-focused, making it suitable for deployment in academic institutions, placement training centers, and self-paced learning platforms. The system demonstrates how AI-driven interview simulation can enhance candidate readiness, confidence, and overall interview performance.

Index Terms—Virtual Interview Assistant, Resume-Based Question Generation, Natural Language Processing, Applicant Tracking System (ATS), Voice-Based Interview Simulation, Automated Feedback, Interview Preparation, Artificial Intelligence.

I. INTRODUCTION

The rapid growth of the information technology sector, the growing pressure in employment circles has focusing more on how crucial it is to get ready properly for interviews [15]. Though schools emphasize theory alongside hands-on tasks, Some folks know a lot, yet turning that into success trips up plenty of learners and those hunting work turning what they know into clear answers that hold together well when asked questions.

Finding a job sometimes means showing skill on paper - yet what happens in the room matters just as much Clear communication matters. What counts is how well ideas connect, thinking straight helps too. The way thoughts link makes a difference because they can talk about what happened before in a clear way, things often work out better Fumbling through questions often trips people up when they face job interviews. Not knowing what to expect slows many down right at the start. Missing practice means stumbling under pressure later on Getting a job remains tough, especially if you have technical skills but face stiff competition.

In recent years, advancements in artificial intelligence and Computers understanding human speech has led to new tools being built Some smart setups can grasp what's being said while also producing responses that make sense. These tools learn patterns without needing every detail spelled out ahead of time Lots of folks now work with machines that understand how people talk. Such tools are used everywhere these days used now in things like automated helpers, tools that suggest what you might like, auto-marking tools plus digital helpers. [1], [2], [3].

What—still, using them to get ready for job talks hasn't caught on much still stuck using basic quiz collections or

scripted practice tests interview platforms that do not adapt to individual candidate profiles. A resume represents a structured summary of a candidate. A person's schooling shows their learning path. What they can do comes through abilities gained over time. Work done highlights real tasks completed. Past jobs give a view of growth step by step. Few tools out there manage what they promise preparing you properly even though it matters so much make good use of what's on your resume. Questions in interviews often come from it usually fixed, bearing little connection to what the person really brings from their past practice, and it feels less real, so it helps less when you need it most. Furthermore, feedback provided by existing platforms is typical, oddly shallow, caring more about how long answers are than what they mean.

Instead of things like how well it fits or makes sense. This study tackles those issues through a suggested approach Virtual Interview Assistant powered by resume data using insights to shape how interviews feel for each person. Looking at patterns helps adjust the approach to the candidate's resume and generating customized interview with questions in play, realism grows through how the system behaves internally. On top of that, machines can grade answers without help. Still, setting up the space takes time before anyone walks in mechanisms for feedback help steer applicants along the way, and improvement is possible. This approach shows how things could work differently and how AI-driven systems can enhance interview preparation. It shifts as needs change, grows when required, yet stays within reach.

II. LITERATURE REVIEW

Nowhere has change been clearer than in how smart tools help people learn and choose work paths. Machines that understand speech and text shape what comes next in education guidance. These shifts started quietly but now affect choices in real ways. Learning systems think differently because computers read more like humans do. Progress here didn't come fast yet it reshapes advice given today. A key part of current studies looks at how machines can judge student work while shaping lessons to fit individual needs. In these setups, software watches what users do, then adjusts responses based on that behavior. Work in this space has appeared often across different fields take smart tutors, computer scoring, or chat helpers—each shows how language processing can assist real teaching and testing work.

Looking into hiring and job readiness, researchers have explored how computers can pull skills from resumes using language tools. Instead of just scanning words, these systems spot key details through pattern detection or smart algorithms. Some setups go a step beyond by comparing applicant backgrounds to role needs automatically. While such tech speeds up sorting candidates, it stumbles when faced with varied layouts or unclear skill contexts. How well it works often depends on how messy real-world resumes tend to be.

A fresh look at automation turns toward creating questions by machine. Earlier work dipped into pulling queries from texts like manuals, journals, papers, or stored facts—using

sentence structure analysis, meaning detection in phrases, also newer deep learning networks built on transformers. Some of these methods do well when tailored to certain topics, fitting classroom needs with decent accuracy. Yet trying them out where job seekers practice interviews, drawing prompts straight from a resume, hasn't drawn much attention so far.

One key area looks at how machines give feedback and judge answers. Studies on grading brief replies or conversations show computers can check if ideas match, stay on topic, or make sense together. Even though such tools work well when tasks are fixed, using them for free-form interview answers remains tough. So far, past work builds a solid base for AI help in prepping interviews - yet leaves room where new solutions could step in.

III. RELATED WORK

Folks building software for job practice haven't cracked the code yet. Some apps pair people together online, tossing out common questions one after another. Tools like Interview-Buddy or Pramp run drills that feel close to real chats. These sessions can help, sure, but only if someone else shows up or the script doesn't stale. Over time, it gets harder to grow without fresh angles or tailored feedback.

Some studies built chatbot tools using fixed scripts or rigid conversation rules. While they handle simple exchanges well, they cannot adjust to a person's unique background. Lately, smarter versions use AI trained on data to run interviews. Still, most pay more attention to managing talk flow than matching questions to someone's work history.

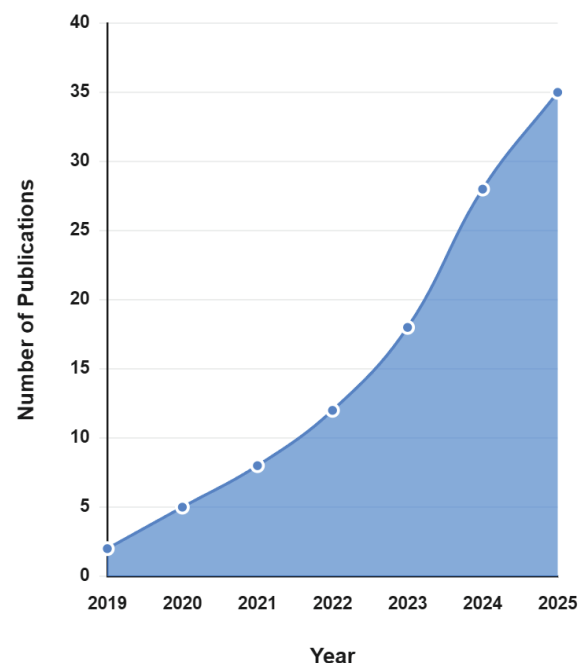


Fig. 1. Year-wise growth in research publications related to AI-based interview preparation and assessment systems.

Looking at what's already out there, seen in Fig. 1, the new tool stands apart—not through one feature but how it brings together resume review, smart questioning, practice sessions, along with clear responses, all working under one system. A fresh angle emerges when these pieces connect, not stand apart—shaping interviews that feel real and fit each person. What sets this apart sits in the middle ground: part learning tool, part smart hiring aid, filling a space most tools miss.

A few research efforts suggest tools powered by artificial intelligence that sort applicants, matching resumes to job needs. While faster hiring comes out of this, the focus leans toward helping employers, not job seekers. These tools rarely highlight ways to get better at interviews or grow skills. What's more, any response they give tends to be hidden in numbers or positions, missing clear reasons behind the results.

IV. PROBLEM STATEMENT AND OBJECTIVES

A doorway opens when theory meets practice interviews link classroom lessons to real jobs. Yet even those who know their subject well tend to fumble under pressure, held back by shaky nerves, poor readiness, and few chances to rehearse tough questions. Most prep routes today depend on live instructors or group drills, which eat up hours, money, and energy while leaving countless learners behind. Feedback, if offered at all, arrives late, vague, or one-size-fits-all rather than sharp, timely, built for growth.

With the rise of online tools for interview preparation now exist, yet they often depend on fixed sets of common questions delivered in rigid sequences. Most skip using a person's actual resume, so the practice questions rarely match what someone truly knows or has done. Instead of deep analysis, feedback tends to count words or spot keywords without judging how clear, relevant, or well-expressed an answer really is.

A fresh approach tackles those issues head-on—introducing a Virtual Interview Assistant driven by natural language processing and smart algorithms. Instead of generic drills, it reads a person's resume carefully, pulling out relevant details to shape unique question sets. Questions come alive through individual profiles, shaped by past roles, education, and skills. When answers arrive, the system dissects them with careful analysis rooted in how machines grasp human speech. Personalized replies meet organized insights, nudging users toward sharper performance under pressure. Confidence grows quietly, built not on guesswork but repeated practice. Communication sharpens each round, refined through targeted input. Built for expansion, the tool fits learners, applicants, and career centers alike. This isn't just another test run. It adapts easily and is meant for real-world demands.

V. PROPOSED SYSTEM AND METHODOLOGY

A. System Architecture

The Virtual Interview Assistant is designed as a modular system in which each component performs a specific function within the overall interview preparation pipeline. This modular architecture improves maintainability, scalability, and

flexibility [10], allowing individual modules to be enhanced or replaced without affecting the entire system.

The Virtual Interview Assistant Fig. 2 follows a structured architecture that transforms a candidate's resume into an interactive and personalized interview experience. The system is designed [11] as a layered pipeline in which data flows sequentially through interconnected modules, ensuring smooth processing and clear separation of responsibilities.

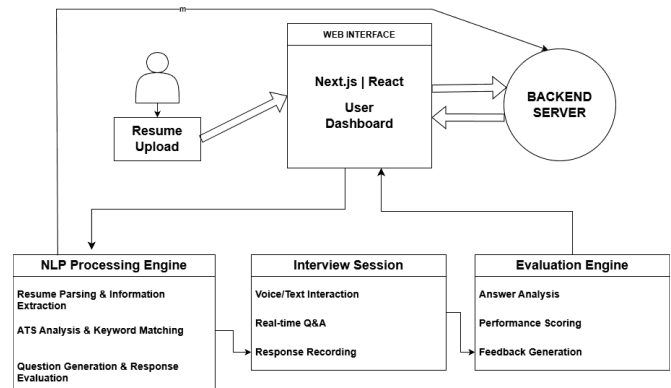


Fig. 2. System Architecture

B. Resume Input and Parsing

The first module handles resume input and preprocessing. Candidates upload their resumes in commonly used formats such as PDF. The system extracts textual content using document parsing libraries and applies natural language processing techniques to identify structured information such as personal details, education, skills, work experience, certifications, and projects [7], [8], [9]. This extracted information forms the foundation for all subsequent modules. Special attention is given to handling variations in resume formats to ensure robustness and accuracy.

C. ATS and Resource Analysis

In this module, the parsed resume content is evaluated against industry-relevant keywords and Applicant Tracking System (ATS) standards [16]. The system identifies missing or weak skill indicators by comparing resume data with predefined job profiles and role-based skill sets [17]. This analysis helps determine the candidate's preparedness for specific roles and provides insight into gaps that may affect interview performance.

D. Resume-based Question Generation

Based on the extracted resume data and ATS analysis, the system dynamically generates interview questions [4]. These questions include technical, conceptual, and human resource-based queries tailored to the candidate's skills, experience, and academic background [5]. Unlike static question banks, this module ensures contextual relevance, making the interview experience more realistic and personalized [6].

E. Virtual Interview Simulation

The virtual interview module simulates a structured interview environment. Candidates interact with the system through text or voice-based inputs, responding to generated questions in real time [2]. The interview flow is adaptive, allowing follow-up questions or difficulty adjustments based on the candidate's responses [5].

F. Answer Evaluation and Feedback

Candidate responses are evaluated using natural language understanding techniques to assess relevance, coherence, and conceptual accuracy. The system generates feedback highlighting strengths, areas of improvement, and suggestions for enhancing responses.

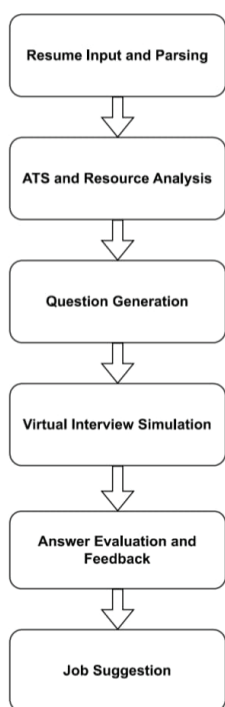


Fig. 3. End-to-end workflow of the Virtual Interview Assistant from resume input to feedback generation.

G. Job Role Recommendation

Based on resume analysis and interview performance, the system recommends suitable job roles and career paths, assisting candidates in aligning their skills with market demands.

The workflow shown in Fig. 3 illustrates the sequential processing pipeline of the proposed system, highlighting how resume data is transformed into personalized interview questions and actionable feedback through AI-driven analysis.

VI. SCORING METHODOLOGY

To provide quantitative feedback and measurable progress tracking, the Virtual Interview Assistant implements a comprehensive scoring mechanism that evaluates candidate performance across multiple dimensions. This section presents

the mathematical formulation and implementation of the performance scoring system.

A. Performance Score Definition

Let us define a performance score P for each mock interview session as follows:

$$P = w_1 \cdot A + w_2 \cdot C + w_3 \cdot T - w_4 \cdot E \quad (1)$$

where the parameters are defined in Table I.

TABLE I
 PERFORMANCE SCORING PARAMETERS

| Symbol | Meaning |
|----------------------|---|
| P | Overall Performance Score |
| A | Accuracy – % of questions answered correctly |
| C | Confidence Level – measured from voice/text analysis (scaled 0–1) |
| T | Timeliness – average response speed (scaled 0–1) |
| E | Errors – penalty score for incorrect logical structure or off-topic responses |
| w_1, w_2, w_3, w_4 | Weights assigned based on importance of each metric |

B. Component Metrics

Accuracy (A): This metric represents the proportion of interview questions answered correctly by the candidate. If a user answers 8 out of 10 questions correctly:

$$A = \frac{8}{10} = 0.8 \quad (2)$$

Higher values indicate better technical correctness and domain knowledge [18]. Accuracy is calculated by comparing candidate responses against expected answer patterns using natural language understanding techniques.

Confidence (C): This metric captures the non-verbal effectiveness and clarity of responses. Confidence is measured through speech analysis, text tone evaluation, or self-assessment ratings:

$$C \in [0, 1] \quad (3)$$

For instance, if acoustic or textual analysis identifies moderate confidence in the candidate's responses:

$$C = 0.6 \quad (4)$$

This component evaluates how clearly and confidently candidates express their knowledge during the interview.

Timeliness (T): This metric measures response promptness and efficiency. It reflects how quickly candidates formulate and deliver their answers relative to expected response times:

$$T \in [0, 1] \quad (5)$$

Faster and more concise answers without compromising quality receive higher timeliness scores. This metric helps

evaluate a candidate's ability to think and respond under time pressure, which is crucial in real interview scenarios.

Errors (E): This penalty component counts critical mistakes such as off-topic responses, logical fallacies, or conceptually incorrect statements. For example, if a candidate makes 2 major errors during the interview:

$$E = 2 \quad (6)$$

The error count reduces the overall performance score, ensuring that quality is prioritized over other metrics.

C. Weight Assignment

The weights w_1, w_2, w_3, w_4 are assigned based on the relative importance of each metric in overall interview performance evaluation. A typical weight configuration might be:

$$w_1 = 0.4, \quad w_2 = 0.3, \quad w_3 = 0.2, \quad w_4 = 0.1 \quad (7)$$

These weights sum to 1.0 for normalized scoring, with accuracy receiving the highest weight as it directly reflects the correctness of responses, followed by confidence, timeliness, and error penalty respectively. The weight distribution can be adjusted based on specific interview types or organizational requirements.

D. Example Calculation

Consider a mock interview session where a candidate achieves the following metrics:

- Accuracy: $A = 0.8$ (answered 80% of questions correctly)
- Confidence: $C = 0.7$ (demonstrated good confidence level)
- Timeliness: $T = 0.9$ (responded promptly and efficiently)
- Errors: $E = 1$ (made one major error)

Using the weight configuration $w_1 = 0.4, w_2 = 0.3, w_3 = 0.2, w_4 = 0.1$, the performance score is calculated as:

$$\begin{aligned} P &= 0.4(0.8) + 0.3(0.7) + 0.2(0.9) - 0.1(1) \\ &= 0.32 + 0.21 + 0.18 - 0.10 \\ &= 0.61 \end{aligned} \quad (8)$$

The resulting performance score is 0.61 (out of 1.0), providing a quantitative measure of interview performance. This score can be tracked over multiple sessions to monitor candidate improvement and identify specific areas requiring additional practice.

E. Score Interpretation and Feedback

The performance score P is interpreted as follows:

- $P \geq 0.8$: Excellent performance
- $0.6 \leq P < 0.8$: Good performance with room for improvement
- $0.4 \leq P < 0.6$: Average performance requiring focused practice
- $P < 0.4$: Requires significant improvement

Along with the numerical score, the system provides detailed feedback breaking down performance across individual metrics, helping candidates understand their strengths and areas needing attention. This quantitative approach enables systematic tracking of progress across multiple interview sessions and facilitates data-driven improvement in interview preparation.

VII. RESULTS AND DISCUSSION

Evaluation of the Virtual Interview Assistant was conducted by observing its performance and user interaction outcomes during live use of the deployed system. The platform successfully demonstrates in Fig. 4 the seamless integration of resume parsing, adaptive question generation, interactive voice-based simulation, and automated feedback generation. Users reported that the system consistently generated interview questions that were relevant to their skills and experiences as specified in their resumes — a key advantage over generic question banks.

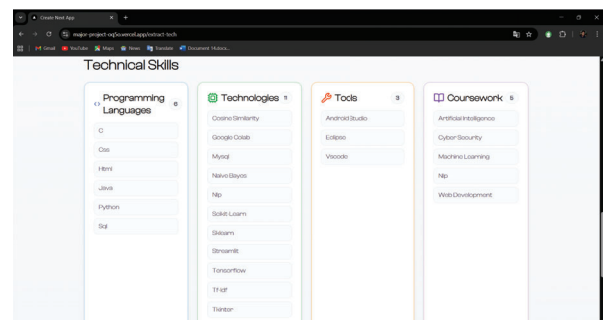


Fig. 4. Keywords Extraction from the uploaded Resume.

The resume analysis component effectively captured structured information from uploaded resumes and influenced question relevance, confirming the utility of ATS-aligned parsing in interview preparation contexts. The voice-based interview simulation provided a realistic interface for users to practice responses under conditions closer to real interviews, which many users rated as more engaging, and confidence-boosting compared to text-only methods.

Feedback delivered by the system highlighted areas such as response clarity, technical coverage, and communication effectiveness. Users noted that the feedback was constructive and helped them understand specific areas of improvement. However, some limitations were observed, particularly in accurately scoring highly varied linguistic expressions and in differentiating between nuanced correctness levels in open-ended responses. The absence of deeper semantic scoring and emotion recognition limits the system's ability to fully simulate human evaluation criteria. Fig. 5 presents a graph-based comparison of the proposed Virtual Interview Assistant with existing interview preparation platforms. Generic mock platforms and peer-based tools demonstrate limited personalization and feedback quality. Chatbot-based systems improve automation but still lack resume-driven contextual relevance. In contrast, the proposed system consistently achieves higher

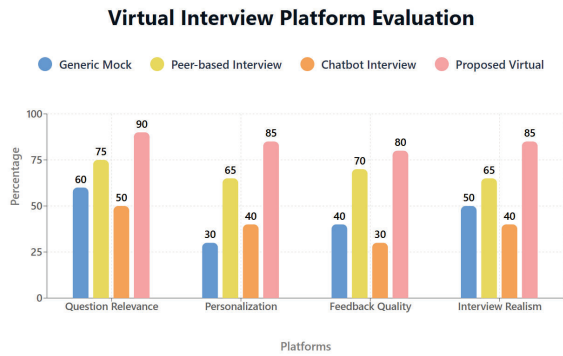


Fig. 5. Comparison of interview preparation platforms across key evaluation metrics.

effectiveness scores across all metrics, particularly in question relevance, personalization, and interview realism. This highlights the impact of integrating resume analysis, ATS-based evaluation, and adaptive interview simulation within a unified framework.

Overall, the results indicate that the Virtual Interview Assistant significantly enhances user preparedness and engagement. Its combination of personalized question generation with adaptive feedback provides a more meaningful interview practice experience than basic automated systems. Future work could incorporate quantitative user studies and performance metrics to further validate efficiency and reliability.

Similar trends in the adoption of AI-based interview and recruitment systems have been reported in recent academic surveys, indicating growing research interest in intelligent employability solutions [16].

VIII. TECHNOLOGY, TOOLS AND REQUIREMENTS

The Virtual Interview Assistant is implemented using a combination of modern web technologies like Python [12], Next.js [13], natural language processing libraries, Hugging Face Transformers [14] and machine learning frameworks to ensure efficiency, scalability, and ease of deployment. The selection of tools is guided by practical considerations such as open-source availability, community support, and compatibility with real-world deployment environments.

A. Software Requirements

The frontend of the system is developed using web technologies such as HTML, CSS, and JavaScript, with Next.js employed to build a responsive and interactive user interface. This framework enables efficient client-server communication and supports dynamic rendering of interview sessions and feedback dashboards.

The backend is implemented using Python-based services integrated with the web framework. Natural language processing tasks such as resume parsing, keyword extraction, and response analysis are handled using libraries including NLTK, SpaCy, and transformer-based models where appropriate. Resume files are processed using document parsing tools such

as PDFMiner, ensuring reliable text extraction from uploaded resumes.

For data storage, relational or NoSQL databases such as MySQL or MongoDB are used to store structured resume data, interview logs, feedback reports, and user profiles. Version control and collaboration are managed through GitHub, while deployment and containerization are supported using Docker and cloud platforms such as Vercel.

B. Hardware Requirements

The system is designed to run efficiently on standard computing hardware. A personal computer or laptop with a minimum of 8 GB RAM, a modern processor, and stable internet connectivity is sufficient for development and testing. For large-scale deployment or voice-based processing, cloud servers with higher computational resources may be utilized.

IX. FEASIBILITY STUDY AND IMPLEMENTATION CONSIDERATION

Before deploying an intelligent interview preparation system, it is essential to evaluate its feasibility from economic, technical, and operational perspectives. The proposed Virtual Interview Assistant has been designed with practicality and scalability in mind, ensuring that it can be adopted in academic and professional environments without excessive resource requirements.

A. Economic Feasibility

The system is economically feasible as it relies primarily on open-source technologies and widely available development frameworks. Libraries used for natural language processing, resume parsing, and web development are freely accessible, reducing licensing costs. Additionally, the modular design allows institutions to deploy only required components, minimizing infrastructure expenses. Cloud-based deployment options further reduce the need for high-end local hardware, making the solution affordable for educational institutions and training centers.

B. Technical Feasibility

From a technical point of view, the proposed system utilizes mature and well-supported technologies. Natural language processing frameworks such as SpaCy and NLTK are capable of handling resume analysis and text evaluation tasks efficiently. Web technologies like Next.js enable the development of responsive and scalable interfaces, while backend services manage data processing and system coordination. The architecture supports both local and cloud-based deployment, ensuring flexibility and reliability.

C. Challenges and Constraints

Despite its feasibility, the system faces certain challenges. Accurately evaluating open-ended interview responses remains complex, as human language can vary significantly in structure and expression. Voice-based interaction introduces additional challenges related to speech recognition accuracy and background noise. Moreover, maintaining fairness and reducing

bias in automated evaluation requires careful model design and continuous refinement. Addressing these challenges is essential for ensuring reliable and ethical system performance.

X. FUTURE SCOPE

The proposed Virtual Interview Assistant provides a strong foundation for intelligent and personalized interview preparation; however, several enhancements can further improve its effectiveness and applicability. One potential extension is the incorporation of advanced speech analysis techniques to evaluate voice modulation, fluency, and confidence levels during interviews. This would enable a more comprehensive assessment of communication skills beyond textual evaluation.

Another promising direction is the integration of emotion and sentiment analysis to better understand candidate behavior under interview conditions. Detecting stress, hesitation or confidence levels could help provide deeper feedback and simulate real interview pressure more accurately. Multilingual support can also be introduced to help candidates from diverse linguistic backgrounds and improve accessibility.

Future versions of the system may include adaptive difficulty adjustment, where the complexity of questions evolves based on real-time performance. In addition, integrating industry-specific interview patterns and organization-level customization can make the platform more suitable for targeted recruitment and role-specific preparation. Long-term analytics and progress tracking can help users monitor improvement over multiple interview sessions.

Further research may also focus on reducing evaluation bias and improving fairness by refining NLP models with diverse datasets. With these enhancements, the Virtual Interview Assistant can evolve into a comprehensive career preparation platform that supports interview readiness, skill development, and informed career decision-making.

XI. CONCLUSION

This paper proposes a comprehensive framework for a Virtual Interview Assistant that utilizes artificial intelligence and natural language processing to provide personalized, resume-driven interview preparation and automated feedback. The system is designed to overcome the limitations of traditional interview training methods by offering a scalable, adaptive, and accessible solution tailored to individual candidate profiles. By employing NLP and ATS-based resume analysis, the assistant generates context-aware interview questions that closely align with real-world recruitment practices.

The proposed system follows a modular architecture integrating key components such as resume parsing, intelligent question generation, virtual interview simulation, response evaluation, and structured feedback delivery. This unified workflow enhances flexibility, maintainability, and scalability, making the framework suitable for deployment across academic institutions and professional training environments. Unlike conventional interview preparation tools, the system emphasizes adaptive learning and continuous performance improvement through data-driven feedback.

From an application-oriented perspective, the Virtual Interview Assistant functions as a product-focused solution supporting placement training, self-paced interview practice, and preliminary candidate assessment. By simulating realistic interview scenarios, the system helps candidates refine communication skills, build confidence, and improve interview readiness within a low-pressure learning environment.

Although the current work is primarily conceptual and does not include extensive experimental validation, it establishes a strong and scalable foundation for real-world implementation. The proposed architecture demonstrates practical feasibility and adaptability, enabling future prototyping, pilot deployment, and commercialization.

Future enhancements may include advanced speech analytics for evaluating fluency and tone, emotion-aware feedback mechanisms to assess confidence and stress levels, and multilingual support to improve accessibility for diverse user groups. Overall, the framework highlights the potential of AI-driven interview simulation to enhance candidate performance and align interview preparation with modern, technology-driven recruitment practices.

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