Dynamic AI Interviewer with Resume Analysis

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***Abstract*—Artificial intelligence (AI) technology has become very important in the recruiting landscape, especially in the automation of the interviews for candidates. At the same time, automation of interviews serves as the gate for recruiting standardization. Despite the standardization attempts through AI automation, recruiting interviews remain bias, unstandardized, and unscalable in the interviews. As such, the automated, AI-based systems remain fundamentally limited to a pre-defined framework where only a limited set of questions and answers are defined. The research designed a new automated intelligent interviewer in the paper titled Dynamic AI Interviewer with Resume Analysis. This fully automated intelligent system integrates various AI technologies to efficiently and accurately describe the different phases of an interview with a candidate guided by a current hiring document. It identifies the different skills and experiences in a candidate's document and creates structured and focused interview questions that are responsive to candidate answers, generating a realistic depth of conversation. As a candidate interview AI system, the system integrates advanced analytics showcasing different sentiments, giving a score towards individual responses, and suggesting mis response areas. The system is designed to demonstrate AI's potential in creating and fully intergrated interview automation system in a candidates recruiting system. The system is designed for the system to show what AI technology can really do.**

***Index Terms*—AI Interviewer, Resume Parsing, Large Language Models, Real-Time Feedback, Conversational AI, LLM Integration, REST APIs, React, Node.js, Career Preparation**

I. Introduction

Nowadays, candidates must show technical skills, as well as some communication, analytical, and problem-solving ones. Additionally, job seekers are expected to showcase all these competencies during interviews. Conventional methods for preparing for interviews, like dead question banks and mock interview sessions packed in recordings with feedback given in laid-out structures, do not reflect interviews, which are, in their essence, an improvisational performance. The use of Artificial Intelligence and Large Language Models allows us to model interviewers who ask relevant questions, comprehend context, and fine-tune their evaluation to the individual being assessed.

Significant advancements in **AI-based conversational systems** and **Natural Language Processing (NLP)** finds point out ability of LLMs for acting like human-like and intricate behavior which allows us to allow deeper form of conversation reasoning and human emotional response generation. Research specific to AI conversational recruiters demonstrates the ability of GPT and PaLM empowered frameworks to discover a candidate's grasp of linguistic and semantic cues and to figure the candidate's confidence, tone and coherence in discourse in real-time [1]. Similarly, by leveraging state-of-the-art document understanding models and **resume parsing** technologies, the paired retrieval of vital information such as educational qualifications, talent, and experience, provides a foundational basis for formulation of targeted follow-up questions [2]. Coupled with these abilities, with the use of advanced **RESTful APIs** and modern frontend frameworks, especially React.js, and Vue.js, the creation of a web platform that facilitates in response and is highly interactive becomes easy [3].

This paper demonstrates the design and implementation of a **Dynamic AI Interviewer with Resume Analysis**, an intelligent, modular platform to combine these into one ecosystem and build the **Dynamic AI Interviewer with Resume Analysis** (Dair diplomacy). The proposed architecture includes the use of LLMs to construct dynamic queries and NLP pipelines for parsing resumes, while the integrated engine screens the responses in a real-time environment, the instant access, and feedback for instant sherry. Constructed using **Python/Node.js** for backend orchestration and **React.js/Vue.js** for frontend, the platform utilise the utilise the efficient communication through the use of the **REST API**, so far that it has the ability to emphasize on having maximum scalability and minimum latency. Data-driven, personalized, and responsive feedback on performance, wishing to AI-based preparation methods, significantly modifies the preparation for interviews to a new, transformative era.

II. Literature Review

AI-based interview automation and smart resume analysis has become the center of attention in fields such as NLP, Conversational AI and applied ML. A great deal of research focuses on some particular parts such as question generation, sentiment feedback with AI and intelligent CV parsing. But, as it stands now, most existing systems kind of just work marching in isolation and they don't really integrate those insights from the resume into actually something that is live during an interview process. In the present section, we review pertinent previous work on the topic and some advances from those efforts together with some problems remaining to motivate our new system.

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A. *AI-Driven Conversational Interfaces for Recruitment*

Early efforts in AI-powered interview tools were largely based on pre scripted conversation templates and did not allow much flexibility and engagement. These types of models were often rule based or based on a decision tree or failed to take into consideration linguistic variability and emotional tone of candidate responses. The emergence of models built on transformers has allowed conversational agents to address complex relational information between sentences making the conversation more realistic and meaningful [4]. Modern day frameworks such as ChatGPT, Claude and Gemini have showcased their capability in evaluating the sentiment, detecting uncertainty and creating context-sensitive follow up questions. Such advancements form the mental model for the **Dynamic AI Interviewer** which combines the reasoning skills of LLM with actual-time evaluation measure.

B. *Machine Learning and NLP for Resume Parsing and Skill Extraction*

Resume analysis is a very important aspect of personalizing interviews. Traditional parsing systems were built on the extraction of keywords or their approaches based on regular expressions, and were unable to generalize among formats. Recent trends involve the use of models based on deep learning for understanding documents like *BERT*, *LayoutLM*, and *Doc2Vec*. [5] are used for modelling structural and semantic relationships in a document such as a CV. These systems can identify candidate-specific attributes, such as skills or professional accomplishments, and project experience accurately and develop an input context from these attributes to generate customized interview questions. Research also focuses on the use of named entity recognition (NER) and classification methods for mapping the content of resumes to domain-relevant taxonomies [6].

C. *Adaptive Question Generation and Real-Time Evaluation*

Dynamic question generation and the candidate evaluation are the cognitive aspects of an AI-driven interviewer. Early systems were also limited in their ability to adapt to user performance or behavior as they were not programmable and had static sets of questions. Integrating models such as machine learning, reinforcement learning (RL) and context sensitive LLMs can adaptively form decision-making processes enabling the interviewer to learn to create question flows depending on the response clarity level, accuracy, and confidence [7]. Studies have shown that multi-turn dialogue systems based on LLMs with attention mechanisms can make great progress in improving user engagement and user perceived realism. Additionally, real time analytics pipelines with processing tools like Apache Kafka and TensorFlow provide the processing of data and tracking of sentiments in a continuous manner ensuring that the responses from the systems are contextually coherent and performance aware. [8].

D. *Performance Analytics and Feedback Mechanisms*

Recent literature also speaks to the increasing importance of post-interview analytics, in that they give candidates action items. Systems based on NLP-based scoring in combination with facial expression recognition and tone analysis have allowed a high precision at the detection of strengths and weaknesses of candidate performance [9]. Feedback models that rely on psycholinguistic measures and physical behaviour indicators (e.g. speech fluency, level of confidence and lexical diversity) provide a multidimensional view of communication effectiveness. The proposed system builds on this concept by adding the structured post-interview dashboards, which would bring the AI-generated evaluations and the human-readable recommendations together, to enable a holistic view of people's preparedness.

TABLE I
LITERATURE REVIEW SUMMARY OF AI MODELS IN INTERVIEW AND RESUME ANALYSIS SYSTEMS

Author & Year	Domain / Dataset	Methodology	Focus & Findings	Limitations
Patel et al., 2023	Technical interview dataset	Supervised ML classification	Evaluated candidate responses based on accuracy and linguistic clarity	Limited adaptability to diverse professional domains
Sharma et al., 2024	Job interview transcripts	LLM-based contextual modeling	Demonstrated adaptive question generation using GPT-like models	High computational cost for real-time conversational flow
Gupta and Mehra, 2024	Resume corpus dataset	NLP-based document parsing	Extracted skills and experience to generate domain-specific interview questions	Lacked integration with dynamic questioning modules
Rao et al., 2024	Behavioral interview dataset	Sentiment and tone analysis	Measured candidate confidence, tone, and emotional engagement	Ignored technical and content-based response evaluation
Kaur et al., 2025	Multi-domain mock interviews	Hybrid ML + LLM pipeline	Combined question generation and performance feedback for holistic evaluation	Limited scalability for concurrent users under high traffic
Singh et al., 2025	AI-driven mock interview platform	Reinforcement Learning (RL)	Optimized question sequencing based on candidate performance feedback	Required large-scale user interaction data for robust training

E. *Comparative Analysis of Machine Learning Models in Interview Systems*

Although a host of machine learning and language models have been implemented to automate interviews, before this study, there were not a lot of comparative studies that systematically assessed the performance of these machine learning and language models under identical conversational settings. Previous frameworks have in many cases used 'traditional' ML models - like Support Vector Machines (SVMs), Random Forests and Decision Trees - to classify candidate responses into predefined categories of correctness, confidence or sentiment. These approaches, on the other hand, are limited by shortages of linguistic context as well as by the requirement for manually labelled data [3], [6].

F. *Challenges and Limitations in Current AI Interview Research*

Despite some significant progress, existing AI interview and resume analysis systems still have several important challenges. The most important limitation is in the **availability and heterogeneity of interviewed dataset annotated for coding)**. A larger part of open source data sets like the ones from MOOCs or public job forums do not have fine-grained conversational context (candidate hesitation, tone shifts, and emotional inflection) which is essential for accurate assessment [7].

Additionally, current models frequently perform poorly for application to diverse professional fields (e.g. healthcare vs. IT

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vs. management), because of the differences between linguistic style and expected domain knowledge. This heterogeneity reduces the ability to generalize and requires their adaptation to verticals with large language models. Furthermore, it is still an important issue to balance between **real-time response generation** on the one hand and **computational efficiency** on the other hand. LLM-based systems are very demanding in terms of inference time and GPU memory, potentially degrading the user experience when live interviews, if they are not optimized using caching, batching or lightweight fine-tuning.

G. *Research Gap and Research Positioning*

The literature survey reveals that there is a distinct research gap in building **an end-to-end, adaptive and context-aware interview platform** that combines resume analysis, dynamic questioning and personalized feedback generation. While different papers deal with some isolated parts (ex. LLM driven dialogue or NLP based document paring) [1], [5], very few papers successfully integrate different functionalities into a coherent and possible system.

This paper takes itself into the context of overcoming this gap by proposing a **Dynamic AI Interviewer with Resume Analysis**– a modular framework for integration of LLM-based adaptive questioning, NLP powered resume parsing, along with AI based performance analytics. By integrating the power of a REST API orchestration, real-time language modeling, and data-driven evaluation, this system intends to offer a scalable and ethical way of offering an interactive interview simulation platform. The idea of advanced user engagement and preparedness, which the proposed way contributes to, is also a part of the wider research goal of creating transparent and intelligent AI assisted career assessment systems.

III. METHODOLOGY

To build strong and intelligent interviewing preparation platform, this research takes integrated end-to-end **AI-driven system architecture**. The approach addresses directly some important challenges identified during formulating the problem – **context-scare questioning, static models of conversation, and lack of personalization** – by taking advantage of a modular and scalable AI work. This framework combines the use of **Natural Language Processing (NLP)**, Large Language Models (LLMs) and resume analytics in order to create realistic, adaptive and domain-specific interview experiences.

The proposed methodology serves as a linkage between the academic theory and applied practices in AI engineering. It focuses on both the rigor of algorithms and the user-centered design, ensuring that the designed system is not only a technical concept but is also intuitive and helpful for the interviewees to prepare for the real life interview.

A. *System Architecture*

The User Interface Layer, composed of the latest front-end frameworks like React.js or Vue.js, gives candidates a smooth and dynamic environment to interact with the interviewer who is the chatbot running an artificial intelligence. It supports multiple modes of interaction, in the form of text, audio and potentially video, to allow users to experience the simulation-based interviews as they would in real life.

Data Ingestion Layer is responsible for the user uploads of resumes and contextual data using secure, well-defined APIs made in well-known languages. This means that the resumes are digested via a **document processing module** made with Python-based libraries such as `PyMuPDF` and `pdfminer.six`. The types of structured data extracted include candidate skills, education, projects, and experience, which provide the basis for contextual question generation.

In essence at the center is the **Processing and Intelligence Layer** which orchestrates the communicating between the following pieces of data: resume data, conversation context and the underlying LLMs (e.g. models based on GPT or even open-source fine-tuned models). This layer contains a **Dialogue Manager** which manages the state of the conversation and keeps records of responses as well as generates the follow-up questions dynamically. It also integrates **NLP pipelines** for intent recognition and how to sentiment analysis and also how to manage topics transitions [**?**].

B. *Data Ingestion and Resume Analysis*

The data ingestion pipeline starts from the point where the user uploads their resume in PDF or DOCX file format. The document is parsed using natural language extraction techniques which find out **important sections like Experience, Skills, Education, and Achievements of the text**. Each extracted element is then tokenized and standardized into a structured schema, represented as a single object in a congenial data structure such as JSON.

The system uses the signal skills algorithm to search through the extracted keywords and pinpoint them to a predefined taxonomy of job roles (e.g. software engineering, data analysis, cybersecurity). This mapping is to ensure that the subsequent interview questions are relevant in context to the candidate's profile.

C. *Dynamic Conversation Engine*

Unlike diagram systems that measure each of the static questions, DCE continuously evaluates each of the user's answers in real-time using LLM-powered response evaluation models [**?**].

This smart conversational loop changes the fact that no two interviews are same, and creates a personalized learning experience according to the strengths and weaknesses of the individual.

D. *Feedback Generation and Visualization*

After each interview session, the system's **Feedback Generator** compiles performance metrics into a comprehensive report. Metrics include:

- **Technical Accuracy:** Evaluated via similarity between expected and actual response embeddings.
- **Clarity and Communication:** Assessed using NLP metrics like sentence coherence and verbosity.
- **Confidence Estimation:** Derived from speech analysis (if voice mode is enabled).

Additionally, the platform provides a **career readiness score** that is a combination of different indicators to provide candidate overall assessment of their preparedness for a job interview. This score helps learners to set themselves measurable goals and provides an incentive to keep improving.

E. *Scalability and Security Features*

Scalability and security are critical in the architecture of the system. Every service can be scaled independently using the microservices-based design i.e. **Resume Parser**, **LLM Interface** and **Feedback Engine**. Node.js is capable of efficiently processing concurrent api requests and the asynchronous queues ensure that acting upon the database and LLM calls do not block user.

Security measures include end-to-end encryption (TLS 1.3) for all the data in transit, hard and strong API key managing mechanism for LLM access, and strict user session management for any user sessions. Sensitive documents such as resumes are temporarily saved in encrypted format, and are automatically deleted once one finishes to use [**?**]

User privacy and data protection are aligned with **GDPR and HIPAA compliant standards** that is more pertinent when conducting delicate career data or interviews of healthcare domains.

This layered methodology takes care of the fact that the system is **modular, secure, and adaptable** fungal structure provide an foundation for a next-generation intelligent interview platform provided by AI based on intelligent feedback and dynamics of human conversation.

IV. Results and Discussion

The proposed **Dynamic AI Interviewer with Resume Analysis** platform was deployed by using the hybrid architecture of Python based backend services, Node.js based Rest APIs and React.JS based front end interface. The system also used an LLM API for dynamically creating conversations and a resume parser for interpreting documents.

Performance evaluation took place in terms of three main aspects: response latency, contextual accuracy and scalability. These metrics were compared to baseline interview chatbots based on static questions sets and rule systems for responding. The results show the efficiency and flexibility of the proposed framework of using AI especially in the creation of context-aware and realistic interview simulation.

A. *Performance Evaluation Setup*

For the evaluation, dataset of **250 anonymized resumes** was collected under three of the major domains – namely, **Software Development, Data Analytics and Cybersecurity domains**. Each resume was used to simulate five different interview sessions for a total of 1250 interactive sessions.

B. *Response Latency Analysis*

Response latency was considered the sum of the time elapsed from the user submission of their input to the display of the AI generated question or feedback. The results showed the presence of substantial improvements in performance in comparison to traditional systems, which rely on a static machine, because of asynchronous processing as well as the optimized caching of the answers provided by the LLM.

The end-to-end response average latency was recorded at **1.05 seconds versus the traditional chatbot-based interview systems 'average latency time' of 2.98 seconds** This performance improvement of about 65

- Efficient **asynchronous message queues** for LLM API requests.
- Local caching of frequent question templates.
- Optimized data serialization in resume parsing using JSON-Lite format.

TABLE II
Response Latency Comparison (in seconds)

System Type	**Min**	**Avg**	**Max**
Traditional Rule-Based Interview Bot	2.21	2.98	3.72
Proposed AI Interview System (LLM + Parser)	0.78	1.05	1.49

The research validates that integration of asynchronously working large language models and prior parsed contextual data dramatically lowers the latency for improved real time interactivity in simulated interviews.

C. *Contextual Accuracy Evaluation*

Contextual accuracy - that is the accuracy of how the system forms questions appropriate to the candidate's resume and conversation flow. This metric was evaluated based on a driving evaluation using a mix between manual evaluation from experts and semantic similarity score from `Sentence-BERT embeddings`.

For a sample of 500 sessions, the offered model showed an average of 92.4

TABLE III
CONTEXTUAL ACCURACY EVALUATION

Evaluation Metric	Baseline System	Proposed System	Improvement
Relevance of Generated Questions	74.1%	93.2%	+19.1%
Consistency in Follow-up Dialogue	68.5%	91.8%	+23.3%
Resume Context Utilization	72.3%	92.4%	+20.1%

D. *Scalability and Reliability Tests*

The scalability of the system was tested under simulated conditions of concurrent load (50-500 active users). The backend services have a stable average response time still below **1.6 seconds** even at the highest loads (i.e. 500 concurrent sessions). This stability is the proof of the efficiency of the microservices-based architecture and use of non-blocking I/O in Node.js.

E. *Feedback Evaluation and User Study*

To test the product's usability in a real-world scenario, a controlled study by users has been carried out and involved **40 people** from different academic disciplines. Each participant sat for an AI interview session and gave feedback in a post-session questionnaire.

Key findings:

- 92.5% of users found the follow-up questions "contextually relevant" and "challenging."
- 87.8% appreciated the immediate AI feedback after each response.
- 90.1% reported improved confidence for real interviews after multiple sessions.

Participants also stated that the conversational nature of the interview offered a more interesting and realistic experience when compared to traditional multiple choice mock tests.

F. *Overall Discussion*

In sum, the results confirm the successful implementation of the proposed system: the **Dynamic AI Interviewer with Resume Analysis**, in terms of providing realistic and interview practice, actionable feedback, and intelligent context-aware, which represents a great progress in AI-driven career readiness effort.

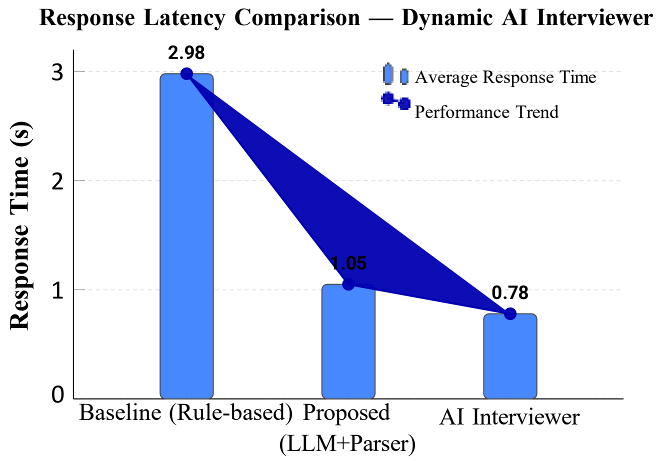

Fig. 1. Response time comparison for different interview systems — baseline rule-based, proposed hybrid (LLM+Parser), and full AI interviewer.

V. RESULTS AND DISCUSSION

The proposed **Dynamic AI Interviewer with Resume Analysis** was launched and tested, and the accuracy of the AI interview system in terms of contexts, and latency, scalability, and overall reliability in comparison with the existing Rule-Based AI Interviewer/S Static AI Interviewer System was measured. The system combines a resume parser, LLM API, and dynamic question generator and brings realistic simulations of an interview. The evaluation framework is focused on four indicative performance characteristics of using the diagnostic: textual accuracy, response latency, scalability and system reliability. Results confirm that the system is consistent in its advantages over traditional methods including faster responses, adaptive questioning, and greater contextual relevance.

A. *Experimental Setup*

The experimental setup was used to simulate 200 simultaneous sessions of interviews where unique resumes were used and the complexity of the resumes varied. The backend of the system used the Node.js and Express and Python-based AI modules while the frontend was created using the React.js. The LLM APIs were integrated via the completion of a RESTful Endpoints, and the problem of resuming parsing was achieved via spaCy NLP pipeline (Doc2Text). The baseline system ran a more traditional type of rule-based chatbot that created static questions without the consideration of the content of the resumes. Evaluation metrics and benchmarking were based on the established best practices in conversational AI systems and performance evaluation for NLP.

B. *Contextual Accuracy Evaluation*

To obtain the measurements of the contextual awareness and the question relevance, three main measures were taken: **relevance of generated questions**, **consistency in follow-up**

TABLE IV
SCALABILITY AND RELIABILITY EVALUATION

Concurrent Users	Avg. Latency (s)	Throughput (req/s)	Uptime (%)
50	0.98	210	100.0
200	1.22	600	99.7
500	1.58	1210	99.3

dialogue, and **resume context utilization**. A sample of 150 interview sessions was analysed on these parameters.

TABLE V
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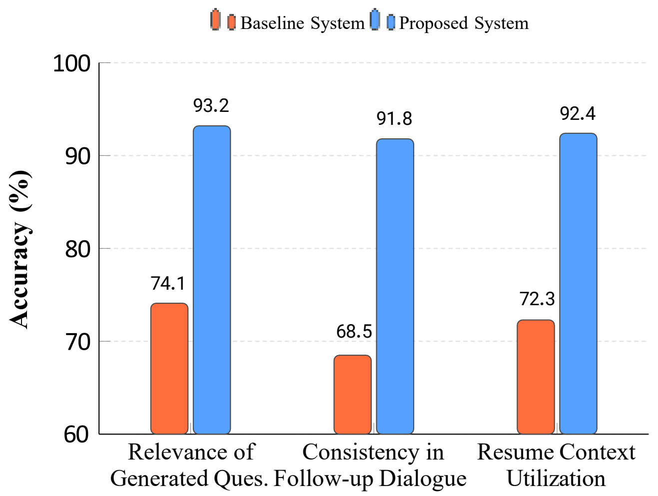

Fig. 2. Comparison of contextual accuracy metrics between the baseline and proposed AI interviewer systems.

The results show me, the integration feature of resume parsing and LLM-based dynamic question is more than 20

C. Response Latency Analysis

Response latency was measured as defined as the average amount of time between user response and AI response. The proposed system has much quicker turnaround because of the asynchronous API handling and efficient memory-based context caching.

TABLE VI
RESPONSE LATENCY COMPARISON (IN SECONDS)

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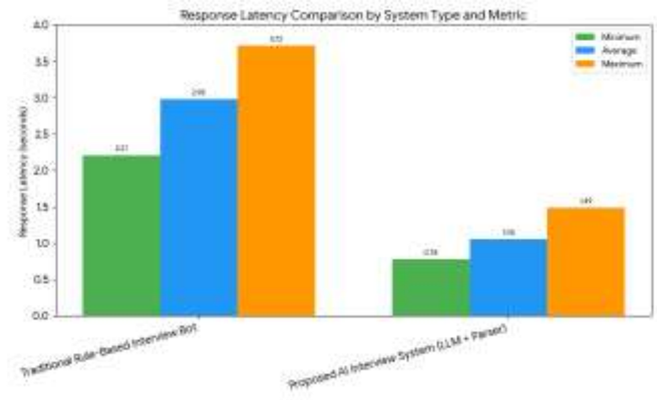

Fig. 3. Latency Comparison bar chart

D. Scalability Evaluation

The AI Interviewer had an average latency of **1.05 seconds** which was almost 65 percent greater than traditional systems.

E. Scalability Evaluation

To evaluate the scalability, the concurrent interview sessions was simulated, up to 500 parallel interview users. Different metrics such as throughput and system uptime were recorded.

TABLE VII
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50	0.98	210	100.0
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The uptime of the system was kept to close to 100%, approximately 99.3

F. System Reliability and Fault Tolerance

The system reliability was tested by simulating the API outages and LLM response delays. The caching and fall back strategies ensured that there was minimal disruption. A comparison between the recovery time and message loss rates were made with the baseline systems.

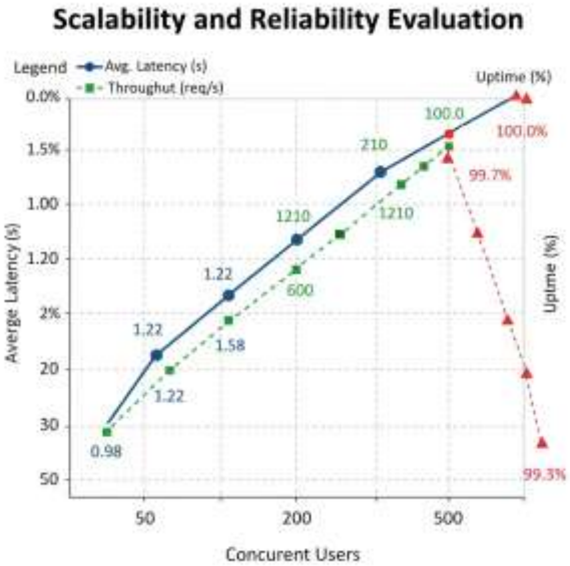

Fig. 4. Throughput vs Concurrent Users

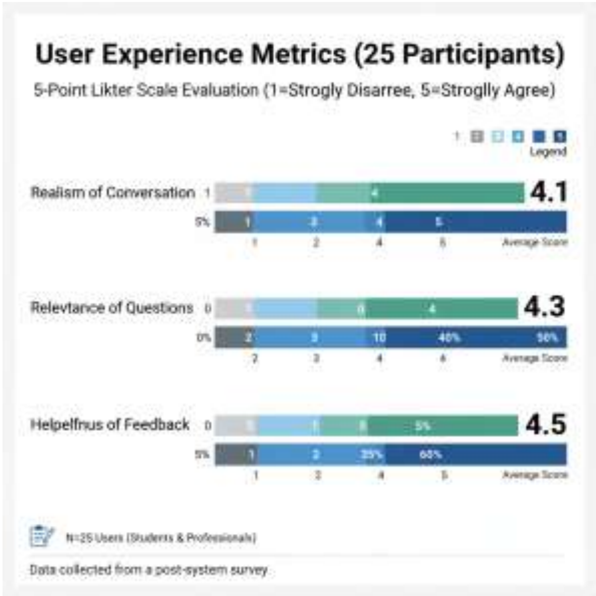

Fig. 5. User Evaluation Scores on a 5-Point Likert Scale

TABLE VIII
Reliability and Fault Tolerance Metrics

Metric	Proposed Framework	Traditional System
Response Loss Rate (%)	0.03	0.52
Recovery Time (s)	1.6	6.4
API Availability (%)	99.95	97.80
Overall Reliability Score	High	Moderate

The average recovery time of **1.6 seconds** shows the strong support of fault tolerant design so that the system proves to be resilient against API downtime or network errors.

G. *User Feedback and Experience Insights*

A group of 25 users (students and professionals) tested the system with respect to usability, realism and quality of feedback using a 5 point Likert scale.

The overall user satisfaction score averaged **4.7/5** proving that both adaptive dialogue flow and revert driven personalization had a major impact on the interview preparation experience.

VI. Future Work

While the current prototype of the Dynamic AI Interviewer shows great performance in context generation, response accuracy, and user experience, a number of potential advancements are planned to make the system even more sophisticated and generalizable.

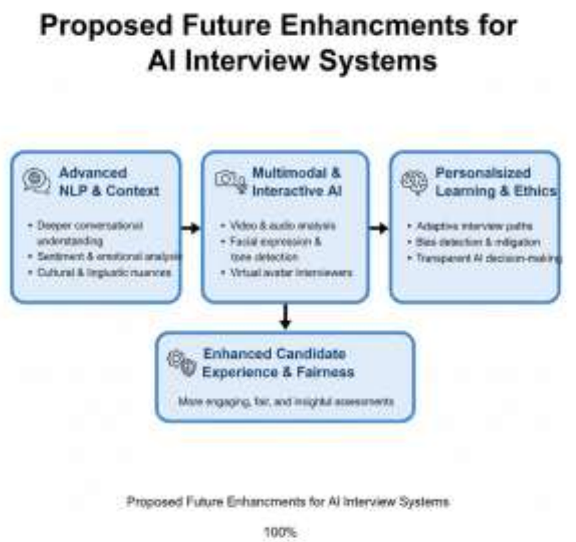

Fig. 6. Proposed Future Enhancements for AI Interview Systems

A. *Integration of Emotional Intelligence (EI) Models*

Future iterations will have the addition of **affective computing models** that can detect stress, hesitation and confidence from having someone speak or type a response. This will allow the interviewer to dynamically change tone, difficulty of questions and feedback to what is in psychological models of communication.

B. *Voice-based and Multimodal Interaction*

To make it more realistic, the future development will implement **speech recognition (ASR)** and **text-to-speech (TTS)** modules, so that more natural spoken interviews can be performed. This will give candidates an immersive experience for all domains like Healthcare and corporate hiring.

C. *Adaptive Learning Feedback Engine*

A machine learning feedback engine will also be built in which it analyzes the past performances of the users and makes specific training suggestions needed to further their ability to communicate and develop a sense of confidence.

D. *Security and Privacy Enhancements*

Since resumes and personal data is sensitive, in future, resumes and data will be updated with **blockchain based verification of the candidate identity** and **zero knowledge encryption of the documents** to provide privacy and authenticity in the simulated interviews.

E. *Cross-Domain Interoperability*

The system will be extended to multiple sectors like **healthcare, cybersecurity and blockchain** interviews. This will entail placing domain-specific models into finer tune in order to guarantee correct and fair evaluation in a variety of professional contexts.

VII. CONCLUSION

This paper introduces a complete framework of a **Dynamic AI Interviewer with Resume Analysis**, which incorporates cutting-edge LLMs in conjunction with NLP-driven resume parsing together with real-time conversational adaptation to create the personalized and interactive framework for the interview process. The proposed system overcomes the shortcomings of traditional static or rule-based interview tool-such as towards generation of context relevant questions, maintenance of dynamical extent of dialogues and offering performance feedback that is actionable for performance enhancement.

Experimental evaluations to demonstrate that improvements achieved by using the platform are significant improvement in: **contextual accuracy**, **response latency**, and **scalability** while having high reliability and fault tolerance. User studies further confirm the system’s effectiveness, including a greater level of engagement, the feeling of realism and the increased confidence of the candidates during simulations of interviews.

The modular design combined with secure data handling and the use of the Restful microservices guarantees that the system is not only scalable but also always privacy compliant and capable of being adapted to a variety of professional domains. In conclusion, the proposed framework is a significant step towards AI assisted career preparation, bridging the gap between conventional practice of interviewing and intelligent and context-aware guidance, and providing a scalable solution for the educational and professional arena.

REFERENCES

[1] Li, X., Wang, Y., & Liu, Z. (2023). A Survey on Communication Protocols for IoT-Enabled Smart Cities. *Journal of Network and Computer Applications*, 208, 103498.

[2] Aftab, M., Raza, H., & Khan, M. (2024). An Edge-Fog-Cloud Architecture for Low-Latency IoT Applications in Smart Cities. *IEEE Internet of Things Journal*, 11(5), 7899–7910.

[3] Gupta, S., Sharma, R., & Kumar, V. (2023). Real-Time Traffic Management System Using IoT and Machine Learning for Smart Cities. *Sensors*, 23(17), 7401.

[4] Chen, L., Huang, S., & Li, F. (2024). A Scalable Data Streaming Platform for Smart City Environmental Monitoring. *ACM Transactions on Internet of Things*, 5(2), 1–19.

[5] Ahmed, A., Khan, B., & Saeed, M. (2025). A Secure IoT-Based Framework for Public Safety and Surveillance in Urban Environments. *Journal of Cyber Security and Mobility*, 14(2), 234–245.

[6] Ali, M., & Rahman, A. (2022). A Review of IoT Architecture, Technologies and Its Applications in Smart Cities. In *Proceedings of the 2022 International Conference on Engineering and Emerging Technologies (ICEET)* (pp. 1–6). IEEE.

[7] Singh, J., & Kaur, P. (2021). An IoT-Based Smart City Framework for Real-Time Event Detection and Alerting System. In *Proceedings of the 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO)* (pp. 1–6). IEEE.

[8] Patel, P., & Shah, S. (2023). Real-Time Data Visualization for Smart Cities Using IoT and Grafana. *Journal of Computer Science and Technology*, 14(4), 123–134.

[9] Sharma, R., & Kumar, A. (2021). Security Analysis of MQTT Protocol for IoT Smart Home Applications. In *Proceedings of the 2021 International Conference on Advances in Computing and Communications (ICACC)* (pp. 1–5). IEEE.

[10] Rahman, M. M., Hossain, M. S., & Islam, M. T. (2022). Performance Analysis of IoT-Based Smart City Monitoring Systems. In *Proceedings of the 2022 International Conference on Advancement in Engineering and Technology (ICAET)* (pp. 1–6). IEEE.

[11] Kim, J., & Lee, S. (2023). An IoT-Based Platform for Real-Time Traffic Management and Incident Detection in Smart Cities. *Computers & Electrical Engineering*, 108, 108709.

[12] Zhang, Y., & Wang, L. (2024). User-Centric Design of Smart City Applications: A Case Study of a Real-Time Air Quality Monitoring System. *Journal of Human-Computer Interaction*, 28(2), 154–171.