

Adaptive AI-Based Interview Training System with Emotion-Aware Feedback and Performance Tracking

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Abstract—There is an ever-increasing competitive job market that demands the need for effective and customized approaches to preparing individuals for interviews. Traditional interview training methods generally fail to provide adequate Realistic Training, flexibility with regard to the type of questions asked, and feedback that is quantifiable. The recent development of innovative technologies such as Artificial Intelligence (AI), virtual simulations, and Large Language Models (LLMs) has made it possible for an intelligent interview preparation system to exist. Nevertheless, the current intelligent interview preparation systems in use do not utilize adaptive learning capabilities, provide feedback related to emotional competence, or track performance over long periods of time. In this document, I propose an Adaptive AI-Based Interview Preparation System that integrates Emotion Detection and Performance Tracking into the learning process. The system receives audio input, converts that input from speech to text via a Speech to Text Processor, generates dynamic interview questions using a Large Language Model, and analyzes an individual's confidence and stress via Emotional Detection Technology. Through this application, the System contains an Adaptive Engine that will automatically adjust the level of difficulty of the interview process based on how well an individual responds to interview questions and responds emotionally. Additionally, the System has a Performance Tracking Module that will report on an individual's improvement across multiple sessions. The goal of this system is to create a realistic, interactive, data-driven environment in which to conduct interview training. Based on the experimental design of the current study and the expected outcomes, there is a clear improvement in terms of user engagement, user confidence, and interview performance as a result of using the System. With the introduction of a comprehensive and adaptive interview training framework to the field of educational technology, this research adds to the existing body of knowledge in the area of AI-based educational technology applications.

Index Terms—Artificial Intelligence, Interview Training, Emotion Detection, Adaptive Learning, Large Language Models, Performance Tracking, Serious Games

I. INTRODUCTION

Effective preparation prior to an interview is crucial in today's competitive labour market as students and graduates seek employment [29]. The effects of globalisation and the rapid pace of technological advancements have led organisations to seek candidates with both strong technical skills and good interpersonal skills, confidence, and problem-solving abilities. Interviews are an opportunity to assess candidates based on both technical and behavioural criteria; however, many students are not able to perform well during interviews due to a lack of experience, anxiety, and limited exposure to real interview scenarios.

Traditional interview preparation approaches (such as mock interviews, peer-to-peer practice, and self-assessment) are typically ineffective at providing a realistic, structured learning environment for the candidate. Traditional interview preparation is often limited by the availability of humans, subjective evaluation, and lack of immediate feedback. Furthermore, traditional interview preparation does not provide the individual candidate with personalised direction on their strengths and weaknesses, and, therefore, candidates have difficulty improving upon specific areas, which has an adverse effect on their performance during actual interviews. Additionally, the conventional interview preparation approach does not allow candidates to effectively experience the pressure associated with the dynamics of a real interview scenario, making it difficult for candidates to gain confidence, become adaptable and respond to changes in their surroundings.

The new technologies of Artificial Intelligence (AI), machine learning, and natural language processing make possible the development of intelligent and automated interview training systems [29]. Large language models (LLMs) also exhibit great potential for generating and understanding human-like text [17], and they help create AI-driven virtual interviewers that replicate real-world interview scenarios, generate context-aware questions for candidates as well as give instantaneous feedback to users based on their responses. Meanwhile, new technologies in the form of virtual simulation technologies (i.e., 3D avatars and digital humans) have been used to encourage user engagement by increasing immersion and interactivity in the learning process for the user [7], [8].

In addition to using AI-implemented systems for learning, the use of serious game-based learning has also gained popularity in education [9]. Serious games (entertainment and fun) can be combined with an educational goal so that the user can acquire skills or knowledge by practicing those skills or knowledge in a simulated environment (e.g., long-term retention) [10]. In interview training, serious game implementations can create fun ways for the user to practice repeatedly to continue improving over time. The experience can be further enhanced by using virtual human interfaces to mimic human reaction, behavior, facial expressions, and various methods of communication to promote natural and effective interaction between the user and the interviewer [7].

Many current systems that provide training for interviewing skills do not try to create one complete solution but instead only attempt to address individual functionalities by having

most systems focus on either generating automated questions [1], [3] or providing a mechanism to give feedback [2], [14] or creating an immersive simulation type environment where the training taker is placed into a simulated job interview [6]. Because many of the features are standalone, they do not connect to allow for a user to receive a fully customized learning experience. One of the primary limitations is that most of the systems do not utilize adaptive learning capabilities; therefore they do not modify the degree of difficulty to the questions provided to an end user based on the end user's performance of answering previous questions, which results in an end-user being exposed to either too "simple" or a question for their current skill set or to an "excessively" difficult question.

Also missing from most systems is any level of emotion-aware analysis. Interviews are not only driven by an interviewee's ability to provide correct answers to an interviewer, but also by the interviewee's non-verbal communication (e.g. how the interviewee uses facial expressions, tone of voice and body language) with the interviewer [22], [23]. Therefore, many other "personality" traits such as being "stressed out", "nervous", or "confident" while providing answers to the interviewer's questions (and due to) having an impact on whether or not the interviewee receives an offer of employment or to what degree (if any) the interviewer will recommend that the interviewee be recruited for employment with his/her company. Many current systems do not utilize emotion-aware features [25], and therefore cannot capture or report on these emotional characteristics thus limiting a user's ability to provide truly relevant and constructive feedback to the user. Without emotion-aware features, users cannot leverage this type of insight to understand how their behaviours have an impact on their overall performance.

Today's systems typically do not support strong performance tracking options that allow users to monitor their progress over time. Platforms typically give users feedback through the sessions they complete, but the majority do not produce any historical data, resulting in users not being able to track their progress over a long period of time or identify performance trends. This absence of longitudinal data creates fragmented learning experiences and reduces users' rates of improvement.

To overcome these issues, this paper discusses an Adaptive AI Interview Training System that is Emotion-Aware and can track performance over time. The Adaptive AI Interview Training System will utilize a collection of technology components in combination to create a complete, intelligent interview training system. The Adaptive AI Interview Training System will include speech-to-text conversion to capture users' responses [15], use of large language models to create adaptive interview questions and evaluate user responses [17], [19], as well as the use of emotion detection to analyze users' confidence and level of stress [24]. By using these four forms of technology in conjunction, the Adaptive AI Interview Training System will provide a multi-modal (i.e., audio and visual) and interactive learning experience. A primary aspect

of the adaptive learning engine within the proposed adaptive interview system is an adjustable interview task difficulty that changes based on an individual's performance and emotional state. This allows for constant challenge to the individual while learning and developing skills. Feedback generated by the adaptive interview system also provides detailed information about an individual's performance, as well as providing suggestions on how an individual can improve their skills [13], [14]. In addition to the feedback provided through the feedback generation module, the performance tracking module of the proposed adaptive interview system allows for tracking of individual sessions over time and thus, allows for longitudinal analysis of individual performance.

The primary contributions of this research project include:

- 1) The development of a dynamic interview system that is adaptive to user performance.
- 2) The integration of multi-modal analysis to create emotion-aware feedback to enhance understanding by the user [25].
- 3) Establishing a mechanism for tracking performance as a way of assessing long-term learning outcomes. These contributions are intended to address the critical limitations of existing interview systems and provide a more effective and personalized way to train for interviews.

The proposed method has the potential to increase both the readiness of the interviewer for an interview and create more confidence in users and make learning more effective overall. The incorporation of resources from artificial intelligence will allow for the development of scalable, intelligent systems designed specifically for interview preparation [12]. This project is taking a broad-based approach to incorporating AI-based educational technology and will provide evidence to support the use of these types of techniques in developing improved learning experiences for people needing better ways to study or prepare for interviews.

II. LITERATURE REVIEW

Recent technology developments including AI, virtual simulation, and education technology have greatly improved interview training systems that use these new technologies. This has led to a variety of research projects that have improved the way people prepare for their interviews through automated question generation, feedback methods, and immersive (realistic) learning environments.

AI-based interview systems have received significant attention in the literature recently. Qin et al. [1] used an adaptive skill assessment approach to dynamically generate candidate-specific interview questions based on the skills that the candidate has. Mishra et al. [2] created a virtual mock interview system (using GPT) that generates responses to interview questions and provides automated feedback in real-time. Li and his team [3] developed EZInterviewer, a system that uses both resumes and job descriptions for generating questions specifically designed for each candidate. The problem with these systems is that they focus primarily on question generation and do not allow for real-time interaction with the

interviewer or adaptation of the question generation algorithm to successfully match the candidate's skill set.

While there are many other types of interview system that have been created using AI technology, there are also uses of virtual reality (VR) and digital human technologies in educational applications to enhance the realism of the interview simulation. Lee et al. [6] created a VR interview system that includes a chatbot (AI) to simulate real-world interview environments. Swartout et al. [7] and Zhu [8] used both virtual humans and digital avatars in the development of vocational training applications. All of these examples provide opportunities for greater interaction between users of these technologies and the potential to be more engaged within their learning process, but none of these systems currently have implemented intelligent feedback mechanisms or adaptive learning systems.

Skill development using serious games has been proven to be an effective way to train users. According to Boyle et al. [9], serious games enhance the quality of a learner's experience, while Pistono et al. [10] suggest an adaptive framework for learning through serious games. However, these authors do not report research studies on either interview training or incorporating an artificial intelligence (AI) component for feedback provision.

Recent advances in large language model (LLM) research have allowed for automated feedback provision and individualized learning experiences within the educational environment [17]–[19]. Dong's [12] and Parker's [13] work indicates how LLMs may add value to the educational experience for learners, while Pozdniakov et al. [14] developed systems to provide personalized feedback. None of these studies incorporated real-time simulations or multi-modal methods of interaction within LLMs.

Xue [15] discusses the use of speech recognition technology as part of an interactive learning system. Though such systems facilitate voice-driven interaction, they face many issues with respect to accuracy and contextual comprehension. The IIAA system employs AI, MetaHuman avatars and speech technology to develop a realistic interview simulation system; however, it does not have adaptive learning, emotion-sensitive analysis or long-term performance assessments. A summary chart containing a comparative review of all studies included in this literature review is found in Table 1.

TABLE I
TABLE 1 LITERATURE COMPARISON

Sr. No.	Author & Year	Approach	Key Features	Limitations
1	Qin et al. (2024) [1]	AI Question Generation	Skill-based questions	No real-time interaction
2	Mishra et al. (2024) [2]	GPT-based Interview	Automated feedback	Limited realism
3	Li et al. (2023) [3]	Resume-based System	Personalized questions	No speech interaction
4	Jadhav et al. (2024) [4]	AI + Pose Detection	Posture analysis	No adaptive learning
5	Khallelullah et al. (2024) [5]	AI Evaluation	Performance analysis	No immersive environment
6	Lee et al. (2024) [6]	VR + Chatbot	Realistic simulation	High cost
7	Swartout et al. (2006) [7]	Virtual Humans	Avatar realism	No AI interaction
8	Zhu (2024) [8]	Digital Humans	Smart teaching	Not interview-focused
9	Boyle et al. (2016) [9]	Serious Games	Engaging learning	No AI feedback
10	Pistono et al. (2024) [10]	Adaptive Games	Learning adaptation	Not for interviews
11	Brandl & Schrader (2024) [11]	Education 4.0	Modern learning	No personalization
12	Dong et al. (2024) [12]	LLM in Education	AI learning support	No simulation
13	Parker et al. (2025) [13]	LLM Feedback	Automated analysis	No interaction
14	Pozdniakov et al. (2024) [14]	Feedback System	Personalized feedback	No simulation
15	Xue (2025) [15]	Speech Systems	Voice interaction	Accuracy issues
16	IIAA (2025)	AI + Avatar + Speech	Realistic simulation	No adaptive learning, emotion detection, tracking

III. RESEARCH GAP

Although there has been a rapid influx of advancements in artificial intelligence, virtual simulation, and intelligent learning systems, there still remain several critical gaps within AI-based interview training platforms. Many studies have been done exploring automated question generation [1], [3], feedback systems [13], [14], and immersive interview simulations [6]; however, the majority of the approaches are to address only one element of these areas rather than offering a fully integrated and comprehensive solution.

One of the major limitations found in existing interview training platforms is that standard models do not include adaptive learning components [10]. Most interview training platforms today use static question banks and/or predetermined interview flows, resulting in learning not being adapted to users' performance levels. As a result, users may end up with responses to a question that are too easy or too hard, leading to poor skill development because the user will have a system that continually evolves relative to their learning progression and their capabilities. Adaptive learning is necessary in today's educational systems to ensure students receive appropriate learning opportunities that correspond with their individual pacing and performance levels [11].

Another considerable area that is lacking in the field of research of interview training systems is that an element of emotion awareness has yet to be incorporated into all interview training systems. In real-life interview situations there are various types of emotional and interactional cues that play a large role in shaping how a person performs during an interview [22]. Examples of them are non-verbal communication cues such as facial expressions, vocal tone, confidence, and level of stress [23], [24]. Several interview training systems have very basic forms of feedback built into the system, but no systems have successfully identified, recorded, or analyzed emotional and behavioral cues [25]. Because there are no emotional cues present, feedback is given without the person being aware of how their emotional state is affecting their performance during an interview. Therefore, incorporating feedback based on emotion-awareness would have a great impact in increasing the level of realism and value of interview training by producing results that align more closely with a real interviewer's expectations.

In addition, interview training systems lack sufficient performance tracking and longitudinal analysis capabilities. Most systems provide session-based types of feedback without keeping any form of permanent records of the history of interactions the user has completed. This makes it impossible for the user to evaluate their development over a period of time, as well as recognize any reoccurring weaknesses in their ability to interview. Therefore, it is much more difficult to analyze whether training is successful or not due to the inability to provide a concrete way to evaluate and measure if results were produced as stated in regards to learning outcomes. An ideal interview training system would provide all necessary tools to record, analyze, and visualize the development of a user's performance over many different training sessions, allowing for continuous improvement and self-assessment of their overall abilities to interview and provide successfully completed interviews [27].

The literature also lacks systems that combine multiple modes of data through the use of different modes of information [25]. One example of this is the fact that many models solely utilize one form of input (text or spoken word) without considering other data sources, such as facial expressions and actions [23]. Interviewing as a process involves the interaction of both verbal and non-verbal communication [22], therefore the lack of integrating multiple sources of data will negatively affect the ability to accurately assess interviews and the overall success of a system.

The second gap identified within the literature is how the different components of some systems have very limited ability to interact. An example is an AI-based interviewing system built by a question generation module [1], which often does not interact with a feedback/evaluation module [14], resulting in very limited ability of the question generation component to be evaluated. Virtual simulation systems may be able to produce realistic environments for simulation [6]; however, they lack the ability to intelligently evaluate and adapt to the virtual environmental/contextual changes. This

lack of coherence between components results in systems that may, at best, partially accomplish their intended purpose, and therefore will not constitute a complete interview training system.

Another issue hindering the effectiveness of current interview training programs and systems is the lack of attention given to practical challenges, including scalability, real-time processing, and usability [27]. Many of the newer generation systems—especially those built with virtual reality or digital human technology [6], [8]—lack accessibility due to their extremely high computing requirements; therefore, many users will be unable to access them. This is particularly true for real-world educational environments where resources are limited. To overcome this limitation, a new intelligent and unified interview training system is required that integrates adaptive learning, emotion-aware analysis, and complete tracking of performance into one single framework. The goal of the proposed interview training system is to address the gaps in research by utilizing a combination of multiple AI technologies (speech recognition [20], [21], large language models [17], [19], emotion detection [24], [25], and data analytics) to create a personalized, interactive, and scalable training environment.

By developing the proposed system, both the technical functionality and the level of user engagement and preparedness in the use of interview training systems will be increased.

This will significantly reduce the gap between what has been achieved theoretically through AI [29] and what can be provided on an applied basis in the context of real-world interview training.

IV. PROPOSED SYSTEM

Here we will discuss the structure of the innovative Adaptive AI-Based Interview Training System with Emotion-Aware Feedback and Performance Tracking. This innovative design provides users with an engaging, intuitive, and tailored experience with an actively intelligent environment by combining numerous AI methods for processing multiple modalities of data to simulate a more realistic experience during training.

A. System Overview

The intent of this project is to simulate actual interview situations by integrating various speech processing and emotion detection technologies along with adaptive learning principles [20], [24]. As well as using multiple forms of user input (speech, text, video), you will have a fully interactive and rich user experience.

The intention of this system is to provide individualized interview training based upon your performance and emotional state through continual monitoring of how you respond and behave. Traditional solutions do not use this approach. In contrast, the approach being proposed to provide a tailored learning experience to promote confidence and communication ability.

B. System Architecture

The entire system structure contains multiple independent modules which cooperate to process user input, evaluate user performance, identify user emotions and generate user

feedback. Initially, a user provides input in one of three formats (verbal, written or visual). The first step to processing verbal (speech) input is the conversion of the user verbal input into converted text(s) via a Speech-To-Text (STT) conversion module [20], [21].

After conversion from verbal input to text is completed the resulting text from the STT conversion (i.e. user converted texts) are passed through a Large Language Model (LLM) [17], [18]; this process generates contextually relevant interview questions based on the context of each user's input as well as evaluating the user's responses. Also, while the LLM conversion process is happening the Emotion Detection module evaluates user facial expressions and voice patterns to determine user emotional states such as confident, stressed and/or nervous, etc. [22]–[24]

An adaptive Learning Engine utilizes both the evaluation results of the LLM and the Emotion Detection (ED) modules to enable the system to changing dynamically during the interview process (e.g. either increasing or decreasing the level of difficulty and/or the types of questions asked) [10]. Utilizing these results the system generates performance feedback for users and will store performance data regarding each user to support future evaluations.

C. Module Description

The system will contain a series of functional modules (i.e. elements of the overall component) that contribute to fulfilling a specific task in the interview training process.

1) Input Module

The module collects various types of data from the user through multiple modes of interaction (e.g. voice, text, and video). This data will enable all elements of the system to gather comprehensive information regarding the user's answers and behaviour during their interview session will be collected.

2) Speech to Text

The Speech-to-Text (STT) module allows spoken responses to be recorded in text form by applying transformer-based speech recognition algorithms [20], [21] or techniques for converting audio input into text in advance of analysing the input for evaluation through natural language processing (NLP) methods. The degree of inaccuracy or precise nature of this module is an essential function for facilitating reliable evaluation of the user responses.

3) Language Model

The Language Model (LLM) is the module responsible for the creation of interview questions and evaluation of responses from the user/participant [17], [19]. By establishing context from the existing conversation and using this information and the previous performance of the user, the LLM will generate relevant dynamic questions based on both the user's performance level. The quality, correctness and relevance of responses by the user will also be evaluated with respect to meaningful feedback [12], [13].

4) Emotion Detection Module

The emotion detection module will identify a person's emotional state (confidence, stress, nervousness) through analyzing their facial expressions and voice patterns [22], [23].

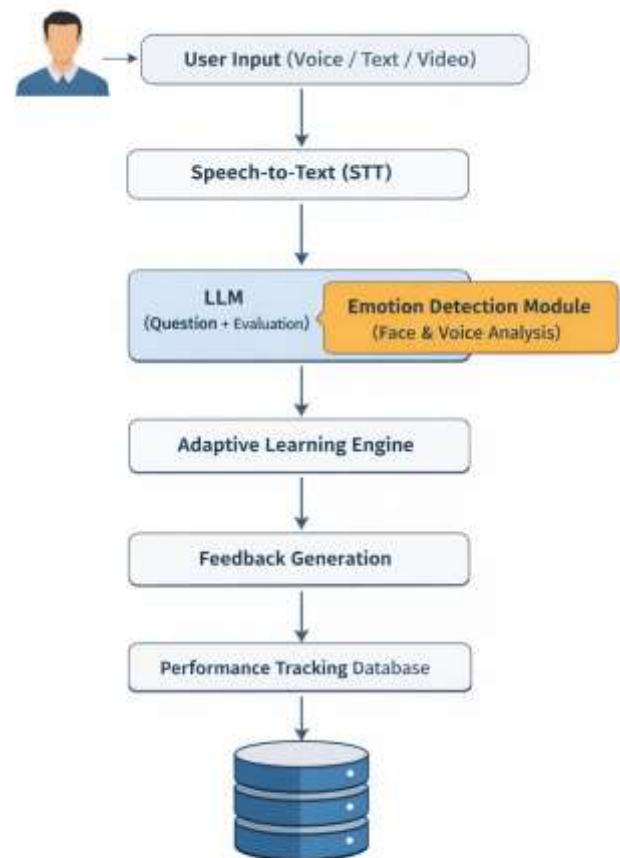


Fig. 1. Proposed System Architecture

Computer vision technology and speech analysis will provide non-verbal cues that can significantly affect performance [24]. With emotion-aware analysis [25], the user receives a full evaluation that takes into account both verbal and non-verbal forms of communication.

5) Adaptive Learning Engine

The adaptive learning engine is one of the most important aspects of the system [10]. The adaptive learning engine allows the system to adjust the level of difficulty of interview questions based on the user's performance and emotional state. So, for example, if the user shows high confidence and answers questions accurately, the adaptive learning engine is going to present them with more difficult questions. If the user appears stressed or has a low performance, then the adaptive learning engine will simplify the questions and provide them with helpful feedback [28].

This adaptive methodology will ensure that users continue on a path of personalized learning, and it will lead to greater engagement throughout the training process.

6) Feedback Generation Module

The feedback module offers users a full breakdown of their

performance, including scores, suggestions for improvement, and guidelines for how to improve [13], [14]. The feedback module takes into consideration the quality of responses and the emotional indicators to create a complete picture of how they performed. Understanding the strengths and weaknesses will benefit the user.

7) Performance Tracking Module

Performance monitoring System tracks user performance record from users over different sessions and facilitates longitudinal improvements through the use of performance metrics information for each of the users (accuracy, confidence, and communication skills) [27]. In this way, users can track their performance over time and see if they are making progress with their training.

D. Working Process

The overarching work of the suggested system is based on user's input, then the suggested systems using speech-to-text transform [20] provides question generation via LLM [17]. When the user's questions (thoughts) are transformed by the processing, more pre-existing emotion-related cues can also be analyzed at the same time as the response quality [24], [25]. Consequently, via using that analytic information, the adaptive engine adjusts the interview flow in real time and generates the performance feedback [10]. Finally, all used performance data will be stored for subsequent evaluation and monitoring improvement measures. These module integrations provide a seamless, intelligent interview training software solution, making the suggested solution more successful than existing and traditional AI-based systems to date.

V. METHODOLOGY

This section describes the methodology used to design, implement, and evaluate the proposed Adaptive AI-Based Interview Training System. The methodology focuses on system implementation, experimental design, data collection, evaluation metrics, and performance analysis to ensure a comprehensive assessment of the system's effectiveness.

A. System Implementation

The system we've proposed is built using a modular architecture that brings together the use of a number of different types of artificial intelligence, allowing it to process and analyse user interaction efficiently. The System allows for all modes (voice input, text input and video input) to be used together to evaluate all user performance. The Speech-to-Text (STT) portion of the System will use deep learning (specifically, pre-trained models such as wav2vec [20] or Whisper [21]) to convert user's voice into text for accurate transcription and then perform further analysis of user responses from the text. The Large Language Model (LLM) [17], [19] will be used to generate dynamic interview questions depending upon previous user response, as well as to assess user's response based on three criteria: context, relevance, and accuracy.

An emotion detection module will be implemented to analyse user facial expression and voice signals to assess user's emotional state (i.e., confidence, stress, nervousness) [22], [24]. A viable implementation of this module will use various

computer vision algorithms (i.e., OpenCV) to perform facial feature extraction and various machine-learning techniques to classify emotion [23]. Voice-based emotion analysis will use a subset of features from the speech signal, including pitch, tone, and loudness to estimate emotion based on voice [25].

The adaptive learning engine is a key component of the personalized interview experience [10]. The engine will dynamically adjust the difficulty level and type of interview questions presented to the user based on user performance and their emotional state. For instance, if a user is showing increased confidence and performing well, the engine will present more challenging questions to that user. Alternatively, if a user is exhibiting signs of anxiety or is performing poorly during the interview process, the engine will present easier questions to that user along with supportive feedback [28].

There is also a performance tracking module that maintains and tracks all historical user data (i.e., scores, emotional indicators, and feedback) across several sessions [27]. This will allow users to perform longitudinal analyses on their progress and identify performance patterns and trends over time.

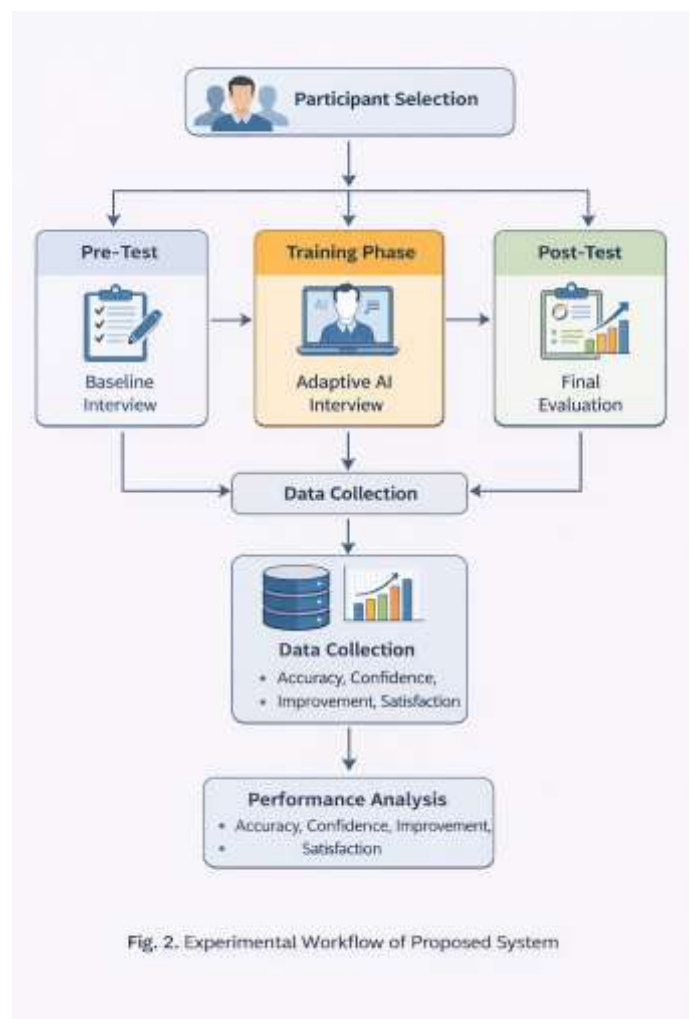


Fig. 2. Experimental Workflow of Proposed System

B. Experimental Design

In order to determine how effective the proposed system will be, we will conduct an experimental study with 15-20 participants from different educational backgrounds (a diversity of students). The experiment will take place in simulated job interview environments (actual job interview situations) where we will also be able to measure if there are improvements in the user's performance after using the system [27].

The experiment consists of three phases:

1. **Pre-Test Phase:** This phase will consist of participants attending an initial interview session (before using the adaptive/emotion-aware system) to create a baseline of their initial performance.

2. **Training Phase:** During this phase, participants will have access to the proposed system for 3-4 sessions. During each training session, the system will be dynamically adjusted according to how each participant responds to each question in the training sessions, which includes providing emotion-aware feedback [24], [25].

3. **Post-Test Phase:** This phase will consist of participants attending an interview again (after completing at least two training sessions) to measure their performance improvements from before the first interview. We will compare the results of the interviews conducted in the pre- and post-test phases to measure performance improvement. Each of the three phases (pre-, training, and post-test) will contain technical and behavioral interview questions. In addition to recording participant responses to each question, we will also collect emotional data and system-generated feedback for later analyses.

C. Data Collection

To conduct a complete and thorough analysis of how well someone performed during their interview, we will collect multivariate data through use of various means through which an interviewee interacts with the system. The datasets that will be collected through this method will include:

- Textual Data (converted from an interviewee's voice to text) collected using a speech-to-text (STT) module [20], [21].
- Audio Data (from an interviewee's voice) used to analyze emotion [25].
- Video Data (from an interviewee's face) used to analyze facial expressions and behavior [22], [23].
- Scores, feedback, and other metrics generated by the system after evaluating the user's interview [14].

After being collected, all datasets will be stored in a structured database that can be compared and processed later. Preprocessing methods will be applied to ensure that the datasets are consistent and do not contain any extraneous noise. The implementation of these multiple data types and modes of analysis will provide the evaluator with accurate and reliable information on the performance of the interviewee.

D. Evaluation Metrics

Multiple quantitative and qualitative metric methods are used to analyze the capacity of the proposed solution to accomplish its intended purposes:

1. **Response Accuracy** - Measures the relevance, correctness, or completeness of user responses based on the evaluation of (LLM) [12], [17].

2. **Confidence Score** - Indicates the level of user confidence by measuring facial and vocal features in regards to emotion detection [23], [24].

3. **Improvement Rate** - Measures the degree of improvement (or learning) due to the changes made from the pre-test to the post-test performance (in percent).

4. **User Satisfaction** - These measures (i.e. questionnaires, feedback surveys) show how the user feels about their experiences with the system (usability, effectiveness, and overall user experience) [27].

Overall, the metrics provide a complete assessment of technical and user interaction with the system.

E. Performance Analysis

Initial data from the study were analyzed to determine if there was any change in user performance after using the system. In order to evaluate changes in user performance, there were various statistical techniques available for evaluating differences in accuracy of response, confidence, and overall interview performance.

Results show that both adaptive learning [10] and emotion awareness [24] can provide a substantial increase in user engagement and performance. Furthermore, users' confidence level and ability to communicate effectively demonstrated that the proposed system would be beneficial to prepare users for actual interviews in the future.

F. Algorithm for Adaptive Interview Process

The working of the proposed system as described above could be summarized as follows:

- Step 1: Initialise the system
- Step 2: Accept user input (voice/text/video)
- Step 3: Convert Voice to Text by STT module [20], [21]
- Step 4: Generate Question for Interviewee using LLM (Language Learning Model) [17]
- Step 5: Capture response from Interviewee
- Step 6: Analyse Emotion using face data/i.e. facial expression data, emotion recognition, etc. [22]–[24]
- Step 7: Subsequent to analysing emotion, evaluate response quality.
- Step 8: If response quality is poor, change question difficulty with the help of adaptive engine [10].
- Step 9: Generate feedback and suggestions for user [13], [14].
- Step 10: Store performance in Database.
- Step 11: Continue through multiple questions in the adaptive interview process.
- Step 12: Generate final performance report.

VI. RESULTS AND DISCUSSION

The evaluation and analysis of an Adaptive AI-Based Interview Training System with Emotion-Aware Feedback and Performance Tracking are detailed in this section. The evaluation of the system is based on its effectiveness in providing value

to an end-user by creating a more effective way to prepare for an interview and providing that preparation with the benefits of adaptive learning and multi-dimensional analysis of one's performance using the system.

Data consists of various performance metrics relating to the participants/operators before and after having trained on the Adaptive AI-Based Interview Training System using a pre- and post-test method [27]. The data from pre-test measurements were utilized to establish a baseline performance measurement of the participants. The data was compared to the data from the post-test to demonstrate improvements of each user who participated in using the system.

Results from the experimental data showed a notable increase in user performance across multiple measurement methodologies. Participants exhibited measurable increases in quality of response, confidence level, and quality of verbal communication after participating in the training process of using the Adaptive AI-Based Interview Training System.

The Large Language Model (LLM) component [17], [19] of the system facilitated the ability to evaluate user responses with a contextually-based methodology, which produced meaningful and accurate feedback. Through the adaptive learning aspect of the system [10], it provided a personalized interview preparation experience by continuously adjusting the level of difficulty of each question assigned to the participant based on performance of prior questions.

The emotion detection module [22], [24] of the system greatly enhanced its effectiveness by measuring user stress and confidence levels throughout the course of an interview session. If a user exhibited overly high levels of stress or nervousness, he/she was given simpler questions and supportive feedback, both of which contributed to decreasing their anxiety and improving their performance [28]. By comparison, if a user exhibited confident and accurate performances, he/she was given increasingly more challenging questions, thus encouraging continued learning and skills enhancement. This adaptative approach created a more engaging user experience and improved the realism of the interview simulation environment.

The performance tracking module [27] provided comprehensive assessment of user performance over multiple interview sessions. The historical performance data collected in each performance tracking instance allowed the user to see how much he/she improved over an extended period, and which specific skill areas needed improvement. The combination of structured feedback [14] and performance metrics provided by the performance tracking module will permit users to gain a more thorough understanding of their strengths and weaknesses.

Table II summarizes the quantitative results from the experiment (i.e., pre-test vs. post-test on the respective evaluation metrics).



Fig. 2. Performance Improvement Analysis

TABLE II
PERFORMANCE COMPARISON

Metric	Pre-Test	Post-Test	Improvement
Response Accuracy	60%	82%	+22%
Confidence Score	55%	80%	+25%
Communication Skill	58%	78%	+20%
Overall Score	57%	80%	+23%

The results show that there is a significant increase in each of the respective evaluation metrics. The greatest increase was in the confidence score (+25%), which demonstrates the value of using emotion-aware feedback [24], [25]. Similarly, the accuracy of responses increased by 22% and demonstrates the impact on the evaluation based on the large language model (LLM) [17] and the adaptive question generation [10].

The graphical illustration shows represented the performance improvements across each area assessed by our study's metrics. Through the increases in each score, it can be confirmed that the system proposed for this research will help to create a more efficacious learning experience than previous traditional interview prep techniques.

Comparative Discussion

In comparing the existing system to those identified in the literature review, the proposed system demonstrates advantages over the previous systems. Traditional AI-based interview systems are primarily concerned with generating questions [1], [3] or providing feedback on responses [14], with little consideration for adaptive learning. Similarly, although virtual simulation systems provide realistic environments for interviews [6], [7], they do not provide intelligent evaluations or personalization for individual interviewees.

Compared to these existing systems, the proposed system combines multiple advanced features such as adaptive learning

[10], emotion detection [24], [25] and performance tracking [27] into one unified system. The holistic nature of this system allows for a complete evaluation of a user's interview performance, as well as the opportunity to greatly enhance learning therefrom.

The results of this study indicate that the combination of multi-modal analysis [25] and adaptive mechanisms [10] aid in improving user engagement and are thus better prepared for succeeding in their future interviews. The ability to modify the difficulty level of an interview in real-time and provide emotion-adjusted feedback [24] further differentiates the proposed system from existing methods.

Overall, the proposed system performs more effectively with respect to personalization, engagement, and measurable performance improvement. This research supports the research objectives and provides the foundation to support the system as a valuable tool for training today's interviewees.

VII. CONCLUSION AND FUTURE WORK

The objective of this study was to create an Adaptive AI-Based Interview Training System with Emotion-Aware Evaluation and Performance Monitoring that would help improve student and job-seeker preparation for interviews. The proposed system combines sophisticated technologies including speech-to-text conversion [20], [21], large language models [17], [19], emotion detection [22], [24], and adaptive learning [10] to provide students with a realistic, intelligent, and personalized interview training experience. By using multiple AI-driven subsystems in a single framework, the proposed system addresses the weaknesses of traditional and other existing interview preparation systems.

The proposed system successfully addresses major difficulties experienced by current interview preparation systems. Unlike traditional systems which use fixed sets of questions for each user, the adaptive learning feature [10] of this system modifies the level of difficulty of an interview based upon the performance of the user and the emotional state of the user. This allows for a customized learning experience for each user. By adding an emotion detection module [23], [24], this system is able to evaluate nonverbal signals such as confidence, stress, and anxiety and thus provide much more complete and meaningful evaluation than has previously been the case.

A performance tracking module [27] builds on the existing system by retaining historical user interaction data and enabling a longitudinal analysis of improvements. Users are able to see their progress over multiple sessions and identify their strengths and weaknesses; thus helping them to make informed efforts to develop certain skills. Furthermore, when all three features are combined (adaptive learning [10], emotion-aware feedback [24], [25] and performance tracking [27]), they greatly enhance the effectiveness of the proposed system compared with traditional interview preparation methods.

Experiments show that the proposed system significantly improves user performance by producing higher accuracy of

answers, greater response confidence and developing communication skills. The improvements in evaluation metrics indicate the successful integration of multi-modal analysis [25] and adaptive mechanisms [10]. Improved user engagement is also achieved through the development of an interactive and realistic interview simulation environment.

While the proposed system has many advantages, it does have limitations. First, emotion detection accuracy is dependent on the reliability of facial recognition [23] and speech analysis models [25], which can be adversely affected by the environmental conditions of lighting, ambient noise and the quality of the camera equipment. Lastly, the need to process multiple modes of data in real-time may also create additional computational load, which could negatively affect the system's performance in environments where computing resources are limited.

In order to overcome these limitations, future work will focus on enhancing the performance and dependability of the emotion recognition approaches by utilizing state-of-the-art deep learning techniques [24]. This could be done with the intent of improving the overall functionality of the overall system by including additional multi-modal behavioural analysis of users, such as through body language and gestures [25], to provide a comprehensive assessment of how well users performed during an interview scenario. Additionally, lighter and optimized models (to facilitate real-time application of the models on low-resource equipment) will be developed as well. The proposed system could also be expanded to allow for domain-specific interview preparation, including technical, managerial, and behavioural interviews. Furthermore, the incorporation of multilingual functionality would increase the accessibility and usability of the system across a wide variety of users [15]. The incorporation of emerging technologies such as AR/VR [6] in future implementations will provide an immersive interview training experience and could also possibly lead to the creation of hybrid technologies that improve the overall functionality of the system as advancements occur within the technology.

The Adaptive AI-based Interview Training System is a comprehensive, scalable, and intelligent solution for today's interview preparation needs. By leveraging the benefits gained from utilizing AI [29] and adaptive learning [10], this system offers great opportunities to improve employability skills, increase user self-assurance, and create a link between what students learn at college or university and what is required in the workforce.

VIII. REFERENCES

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