



DESIGN AND EVALUATION OF AN AI-BASED MOCK INTERVIEW SYSTEM FOR ENGINEERING STUDENTS USING NLP AND GENERATIVE AI

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ABSTRACT

Interviewing performance is a crucial milestone in engineering students' transition into the world of work. Despite having good technical knowledge, students find interviewing an area of difficulty during job placements. Traditionally, interview training involves resource-intensive interviews amongst peers and with professors who can vary in quality of the feedback offered. This paper presents an AI-assisted mock interview system design that uses NLP technologies for resume parsing and response evaluation, and AI for generating dynamically changing questions, specifically to help engineering students overcome their difficulties in preparing for interviews. The system architecture consists of four modules: resume and profile parsing, dynamic question generation, multi-dimensional response evaluation (response content, language skills, and delivery/confidence), and a structured feedback reporting module. These features make up an interview process that is scalable, repeatable, and judgment-free. The literature includes considerable research on developing mock interview systems for general employability and IT graduates. However, we found a gap in incorporating structured evaluation of language proficiency into the interviewing simulation systems, which were designed specifically for engineering students. This paper presents a methodology for designing a single-group pre-test/post-test pilot study to evaluate the effectiveness of our system and to present possible.

KEYWORDS: Natural Language Processing, Generative AI, Mock Interview, Engineering Education, Language Proficiency, Interview Confidence.

INTRODUCTION

The transition from student to practitioner is the most crucial phase in an engineering student's career, and the job interview is the single most crucial step in that transition. Many engineering students struggle to perform well in interviews despite strong technical skills because technical expertise alone is often insufficient. Several factors contribute to this, but the most common are a lack of communication skills, limited interview experience, and low confidence in one's abilities due to inexperience. Much research has examined technology-assisted interview preparation, particularly when one-on-one instruction is unavailable to large numbers of students.

Traditional methods to prepare students for interviews, including career counselling, peer-organised practice interviews, and faculty-led practice interviews, have limitations in terms of availability, scalability, potential biases, and the level of practice they provide. These methods also often do not allow students to practice multiple times or receive detailed feedback to improve and track their progress. Researchers are interested in utilizing AI to overcome these barriers and offer students an accessible, standardized practice experience (Crutsinger & Herrera, 2022).

In recent years, researchers have done substantial work on AI-assisted mock interview systems. Early work focused on analyzing candidates' recorded responses (Chou et al., 2022), while later systems designed their own interaction-design

frameworks for mock interview support (Miao et al., 2020). Some more recent works expand the possibilities of such systems in different directions, including the use of computer vision in combination with NLP and generative AI to analyze both language and expression (Sharma et al., 2025), the use of pose-based interactions to interpret the body language of the candidates (Jadhav et al., 2024), and the analysis of emotions and confidence scores of the candidates during the interview responses (Amrutha et al., 2024). Other works examine the effects of such systems, including their influence on students' readiness and confidence levels (Gomez et al., 2025) or on graduates' employability rates (Amarasena et al., 2024). As shown by the wide range of recent contributions, interest in the area is growing. As a result, adaptive AI mock interview generators (Singh et al., 2026), automated response analysis frameworks based on generative language models (Uppalapati et al., 2025), and virtual interview developers (Mishra et al., 2024) have also emerged recently.

Meanwhile, another body of research has explored the progress of Natural Language Processing as a foundational technology for such systems. NLP refers to the ways computers can analyze, process, and generate human language (Chowdhary, 2020). Improvements in NLP, such as part-of-speech tagging algorithms and error-driven learning approaches (Brill, 1995), as well as the broader field of language understanding and generation (Hirschberg & Manning, 2015), have enabled various



language-oriented educational software. Some of these works highlight the value of NLP and speech processing in evaluating language-related skills (Chapelle & Chung, 2010), facilitating teaching and learning practices overall (Litman, 2016), and helping students with speech and language disorders improve their conversational ability (Habib et al., 2019). Recent studies further include opportunities for NLP to evaluate English-speaking competency, such as the creation of scoring models for English language proficiency (Li, 2026), self-learning systems for evaluation of English-speaking skills (Guo, 2023), and the investigation of effects of NLP-enabled practice on EFL learners' language production accuracy, fluency, and flexibility (Zhang et al., 2026). Together, these articles illustrate the growing role of NLP in language-oriented education and, therefore, its potential value in teaching students interview skills, particularly since such practice also involves assessing students' language proficiency. Earlier foundational work on speech and language processing for large-scale communication services has advanced this field (Cox et al., 2000).

Although this work has been done, most existing work focuses on general employability or IT graduate cases. It pays less attention to the communication-specific and technical articulation requirements of engineering students, as well as integrating language-proficiency evaluation as a key criterion alongside technical content. The purpose of this paper is to propose to design an AI-based mock interview system for engineering students and outline the plan for evaluating its effectiveness in future work. The system uses NLP techniques for resume parsing and response evaluation, and generative techniques for dynamic question generation and conversation, simulating a realistic and adaptive interview. In addition to describing the system's structure, the paper proposes an evaluation methodology and discusses the system's benefits, pedagogical implications, and limitations.

1.1 Motivation

This research is motivated by three factors: the apparent lack of employability among technically trained engineers, the limited scalability of interview coaching, and the rapid evolution of conversational generative artificial intelligence. Engineering colleges have the twin challenge of graduating technically competent engineers as well as teaching them to have good communication skills and interview techniques – which is not always prioritized in technical education.

1.2 Problem Statement

Existing interview preparation resources to which engineering students have access tend to be non-adaptive, require significant resources, or offer inconsistent levels of feedback. An accessible, scalable, educationally sound system is needed that can simulate realistic interview conditions, provide objective and consistent feedback, and allow practice without relying on the availability of a human interviewer.

1.3 Objectives

This study aims to:

1. Design an AI-driven mock interview system that integrates NLP-based resume analysis, generative AI-based dynamic question generation, and automated response evaluation.
2. Identify appropriate NLP techniques for assessing candidate responses across dimensions of language proficiency, content relevance, and confidence.
3. Propose a structured evaluation plan — including study design, participant criteria, and analysis methods — for empirically assessing the system's effectiveness in future work.
4. Critically examine the anticipated limitations of AI-based interview evaluation, including potential biases and the boundaries of assessing soft skills through automated means.

1.4 Scope of the Study

This study presents the design of a text-based mock interview simulation system for campus placements of final-year engineering students (Computer Science and Electronics/ECE) based on core technical and HR/behavioural question types. This paper describes the system architecture and a proposed evaluation methodology; however, empirical validation of the pilot study described in Section 4 has yet to be carried out and is identified as the main thrust of future work (Section 7). Video-based nonverbal analysis is also beyond the current design scope and is considered for future work.

1.5 Organization of the Paper

The remainder of this paper is organized as follows: Section 2 briefly summarizes related work on artificial intelligence interviewers and the use of natural language processing tools in language learning and testing. In Section 3, we present our system design. Section 4 describes the proposed study plan and analysis techniques. In Section 5, we discuss the expected results based on related work. Section 6 addresses the limitations of our work and presents conclusions and recommendations for further work.

2. LITERATURE REVIEW

This section describes related work in two respects: (i) AI-based mock interview systems, ranging from simple performance analysis tools to more involved multimodal dialogue systems, and (ii) Natural Language Processing in language education and assessment, which constitutes the linguistic evaluation part of such systems. The section concludes by describing the research problem addressed in this paper.

2.1 AI-Driven Mock Interview Systems

Research into AI-powered mock interview platforms has advanced significantly in recent years, shifting from single-purpose performance analysis tools to complex multimodal systems. Chou et al. (2022) describe an early AI-based interview simulator that analyzes an interviewee's performance based on recorded responses. Earlier in 2020, Miao et al. addressed the same topic from a human-computer interaction perspective,



discussing the application of goal-oriented design theory to build a mock interview application. Both works show that the design of such software is not limited to performance analysis but can also affect the user experience at a fundamental level.

These successive studies have expanded the scope of the evaluation criteria adopted by these platforms. The study by Jadhav et al. (2024) includes a mock interview simulator that implements pose-based interaction and uses AI to evaluate responses. Similarly, Sharma et al. (2025) suggest developing a platform that uses computer vision, natural language processing, and generative artificial intelligence. This indicates the propensity of researchers towards adopting multiple approaches for evaluating the candidate's performance by considering verbal and non-verbal aspects of the communication process. In contrast, Amrutha et al. (2024) focus on the emotional and confidence aspects of a candidate's performance during a mock interview using AI-based emotion and confidence detection. The study highlights the relevance of considering non-verbal aspects of communication during a placement interview, as in real-life scenarios where a candidate's technical competencies are insufficient for recruitment.

Other studies have explored the architecture and adaptability of these systems. Mishra et al. (2024) reported developing a virtual mock interview platform, while Singh et al. (2026) proposed an adaptive mock interview generation system that tailors the flow of questions to the candidate. This design principle closely aligns with the dynamic, generative-AI-driven

questioning approach used in the present study. Uppalapati et al. (2025) further elaborated on this approach by using generative language models to automatically evaluate interview responses, illustrating the growing role of LLMs not only in question generation but also in scoring and feedback generation.

Several researchers have used such systems in their research. Crutsinger and Herrera (2022) explored how best to use such a resource in mock interviews to improve professional skills beyond technical skills in a professional setting. Gomez et al. (2025) sought to determine the effect such a system would have on students' readiness and confidence before an interview. Amarasena et al. (2024) created a sophisticated mock interview system designed to improve the employability of new IT graduates by demonstrating its value in improving students' performance after graduation.

Together, this body of work shows a clear progression from basic performance assessment through multimodal (verbal, visual, and emotional) evaluation to adaptive, generative-AI-driven question flow, with increasing emphasis on impact on student confidence and employability. However, most of these systems are evaluated in general employability or IT-graduate contexts, with limited emphasis on engineering students per se or on incorporating structured language-proficiency assessment as an integral evaluation criterion alongside technical and behavioral analysis. Table 1 summarizes the reviewed AI mock interview systems and their primary focus.

Table 1: Summary of Reviewed AI-Driven Mock Interview Systems

Study	Year	Primary Focus / Technique
Chou et al.	2022	Performance analysis of recorded mock interview responses
Miao et al.	2020	Interaction design of AI mock interview application (goal-directed design theory)
Jadhav et al.	2024	Mock interview simulator with pose-based interaction
Sharma et al.	2025	Multimodal platform combining computer vision, NLP, and generative AI
Amrutha et al.	2024	AI-based emotion and confidence analysis in mock interviews
Mishra et al.	2024	Virtual mock interview platform development
Singh et al.	2026	Adaptive, AI-powered mock interview question generation
Uppalapati et al.	2025	Generative-language-model-based automated response evaluation
Crutsinger & Herrera	2022	AI resources for broader professional skill development
Gomez et al.	2025	Effect of AI mock interviews on student readiness and confidence
Amarasena et al.	2024	AI mock interview platform for enhancing IT graduate employability



2.2 Natural Language Processing in Language Education and Assessment

The evaluation component of any AI-powered mock interview system relies heavily on the NLP (Natural Language Processing) techniques, which are used to assess the quality of the obtained answers and responses. Chowdhary (2020) provides a complex explanation of the basic approaches, which form the basis of any modern language-processing application, ranging from parsing and semantics to language generation. However, in Brill's (1995) seminal work on transformation-based error-driven learning applied to part-of-speech tagging, one can see the origins of rule-learning methodology that was later supplanted by probabilistic and neural approaches currently used in NLP. The advancements of the field and its practical applications are further discussed by Hirschberg and Manning (2015), who demonstrate how the field's progress is directly linked with the variety of language processing tasks that can be accomplished.

In language education specifically, NLP and speech-processing technologies have long been acknowledged as having great potential for language assessment (Chapelle & Chung, 2010) and for enhancing teaching and learning processes generally by providing automated, language-aware feedback (Litman, 2016). Cox et al. (2000) frame speech and language processing within large-scale communication services, noting the maturity of the underlying speech technologies that interview systems draw on to provide real-time transcription and analysis. Targeted applications in assessing spoken English proficiency include Li's (2026) modeling of an English-speaking scoring system grounded in NLP techniques, and Guo's (2023) proposing of an evaluation method for a self-learning spoken English system – both of which are directly analogous to the automated language-proficiency scoring that an AI mock interview system would need to carry out. Zhang et al. (2026) build on this line of investigation by exploring how NLP-based tools affect EFL learners' speaking accuracy, fluency, and adaptability, finding evidence of NLP-driven improvements in spoken-language skills that applies directly to interview coaching contexts. Habib et al. (2019), in turn, examine AI technologies for enhancing communication skills amongst students with speech and language needs, pointing to the accessibility and inclusivity of the automated, judgment-

free tools that such practices can offer – which is relevant to interview-anxious students more generally.

2.3 Research Gap

While the reviewed literature shows significant progress on both fronts (increasingly sophisticated AI-based mock interview platforms and increasingly capable NLP-based approaches to language assessment), these two fields have rarely been brought together with a focus on the requirements for engineering students, who typically face a combination of technical and general communication competence in their interviews. While existing mock interview systems utilizing some form of multimodal or emotional analysis (Jadhav et al., 2024; Sharma et al., 2025; Amrutha et al., 2024) have rarely focused on the structured NLP-aided language-proficiency assessment, and research into NLP-based language assessment (Li, 2026; Guo, 2023; Zhang et al., 2026) has largely been divorced from the context of an interview simulation, this paper proposes a system using generative AI to ask adaptive questions and assess language proficiency, content relevance, and confidence in line with the specific demands of engineering interviews.

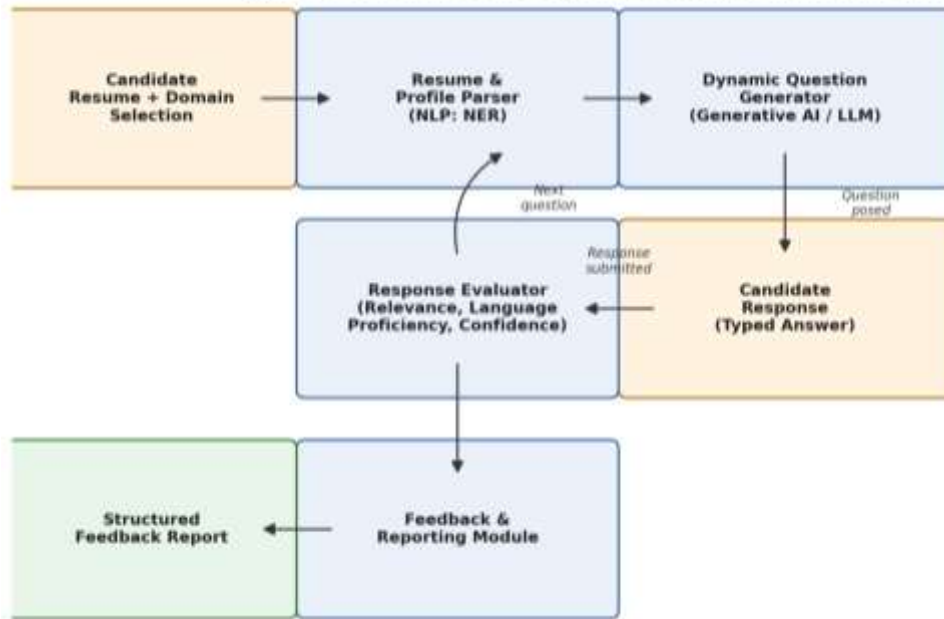
3. PROPOSED SYSTEM DESIGN AND ARCHITECTURE

This section describes the proposed AI-driven mock interview system and the NLP and generative AI techniques employed at each stage of its architecture.

3.1 System Overview

The proposed system consists of four modules namely: (i) Resume and Profile Parser, (ii) Dynamic Question Generator, (iii) Response Evaluator, and (iv) Feedback and Reporting module. The candidate uploads the resume and selects the interview domain (core technical, HR/behavioral, or role-specific). The system conducts an interview with turn-by-turn question generation based on the candidate's response and provides a feedback report at the end of the session. Figure 1 depicts the proposed architecture and the information flow among modules.

Figure 1. Architecture of the Proposed AI-Driven Mock Interview System



3.2 Resume and Profile Parsing

The resume parsing module makes use of NLP-based Named Entity Recognition to extract relevant information from a candidate's uploaded resume. The information could include technical skills, project names and descriptions, academic qualifications, and experience. This parsed information is then used in two ways: as a contextual guide for the question generator to ask project- and skill-specific questions and as a reference point to determine the relevance of a particular response.

3.3 Dynamic Question Generation

Question generation is performed using a generative artificial intelligence (AI) model, in the form of a GPT-class LLM (large language model) that is accessed through an application

programming interface (API), which is prompted with the candidate's parsed profile, chosen interview domain, and history of the conversation. This allows the system to ask follow-up questions that build on the information in the parsed resume, such as follow-ups on the projects listed, as well as to prompt the candidate to provide further detail on a vague or under-specified answer, thus simulating the ad hoc question-asking of human interviewers (Singh et al., 2026; Uppalapati et al., 2025).

3.4 Response Evaluation

Each candidate response is designed to be evaluated along three dimensions, drawing on established NLP techniques. Table 2 summarizes these dimensions, the techniques used, and their purpose.

Table 2: Response Evaluation Dimensions

Dimension	Technique	Purpose
Content Relevance	Semantic similarity scoring via sentence-embedding models (cosine similarity against a reference/ideal-answer embedding)	Measures how directly the response addresses the question asked
Language Proficiency	Automated grammar and fluency checking, vocabulary range analysis, coherence scoring	Measures grammatical accuracy and overall quality of expression
Confidence and Delivery	Sentiment/tone analysis on typed responses (lexical and phrasing cues, e.g., hedging language, assertiveness, completeness)	Estimates the candidate's perceived confidence from response phrasing



Content Relevance — assessed via semantic similarity scoring between the candidate's response and a reference/ideal-answer embedding, using sentence-embedding models to compute cosine similarity.

1. **Language Proficiency** — assessed via automated grammar and fluency checking, vocabulary range analysis, and coherence scoring, drawing on techniques consistent with NLP-based spoken/written language assessment (Li, 2026; Guo, 2023).
2. **Confidence and Delivery** — assessed via sentiment/tone analysis applied to the candidate's typed responses, using lexical and phrasing cues (e.g., hedging language, assertiveness of phrasing, response completeness) as a proxy for perceived confidence, consistent with prior work on AI-based confidence analysis in mock interviews (Amrutha et al., 2024).

The system's design is text-based: candidates type their responses to the prompts, which are then directly evaluated using the NLP techniques described above. We believe that speech-based interaction, utilizing Automated Speech Recognition (ASR) transcription and paralinguistic indicators such as speech rate, filler-word frequency, and pause patterns, would be an interesting extension to this architecture; however, it is not part of the scope of the current design. Thus, the Confidence and Delivery dimension in the current design evaluates sentiment/tone in typed responses, as opposed to evaluating paralinguistic speech patterns. A full evaluation using paralinguistic speech cues is discussed as future work in Section 7.

3.5 Feedback and Reporting

At the end of each session, the system produces a feedback report summarizing performance across the three evaluation dimensions, highlighting strengths and weaknesses (e.g., recurring grammatical errors, insufficient elaboration, or irrelevant answers) and offering suggestions for improvement. This would allow multiple practice iterations, addressing the scalability/repeatability problem of the mock interview coaching described in Section 1.2.

4. PROPOSED EVALUATION PLAN

This section presents a structured plan for empirically evaluating the proposed system's effectiveness. As noted in Section 1.4, this evaluation has not yet been conducted; it is proposed here as the basis for future empirical work (Section 7).

4.1 Study Design

The proposed study will adopt a single-group pre-test/post-test design, using final-year engineering students pursuing computer science and electronics/ECE as the target population. This design is more appropriate than an alternative human-evaluator design. The latter design would require recruiting and training independent human raters to evaluate the initial study before conducting the main experiment. However, this design would help measure changes in confidence levels and evaluation scores over time.

Participants (proposed): N = 40 final-year engineering students, recruited via voluntary sign-up (e.g., through an announcement in a placement-training or technical communication course). This sample size is intended to be large enough to support basic paired statistical testing while remaining feasible for a single-department pilot study.

Procedure (proposed): The participants would be asked to perform three mock interview sessions using the system over the course of two weeks (roughly every four or five days, to allow them to reflect on the feedback before proceeding to the next stage without losing the thread of the training). Before the first session, they would be asked to fill out a short self-evaluation survey on their interview confidence. After the last session, they would be asked to fill out the same self-evaluation survey again, as well as a brief post-study questionnaire regarding their experience with the system. In line with the single-group design discussed above, the proposed study would not involve conducting a human-evaluator interview as a benchmark; comparing the results of the training to an interview with a human interviewer is left as an option for further research (see Section 7).



Table 3: Proposed Pilot Study Design

Study Design and Methodology – Key Details	
Parameter	Planned Value
 Design	Single-group pre-test/post-test
 Population	Final-year Computer Science and Electronics/ECE engineering students
 Sample size	N = 40
 Recruitment	Voluntary sign-up
 Number of sessions	3
 Study duration	2 weeks
 Pre/post measure	Self-reported interview confidence (5-point Likert scale)
 Additional measure	AI-generated evaluation scores per session (relevance, language proficiency, confidence/delivery)
 Qualitative measure	Post-study questionnaire on perceived usefulness and limitations

4.2 Planned Metrics and Data Analysis

The proposed study would collect three categories of data: (i) pre/post self-reported interview confidence (5-point Likert-scale survey), (ii) AI-generated scores across the three evaluation dimensions, tracked across sessions to assess improvement, and (iii) qualitative feedback via a post-study questionnaire on perceived usefulness, ease of use, and any noted limitations.

The quantitative findings would be analyzed using paired-samples t-tests to compare confidence scores before and after the intervention and repeated-measures ANOVA (or trend/slope analysis if session-to-session data are unavailable) to examine changes across the three practice sessions. The qualitative results would be analyzed using thematic analysis to extract common themes that highlight the system's strengths and weaknesses based on participants' responses to the post-study questionnaire.

5. DISCUSSION: ANTICIPATED OUTCOMES

This paper describes a system design and proposes an evaluation plan. This section describes expected outcomes of the system design under discussion, contrasting these to similar findings of the closely related work considered in Section 2 — these are expectations that the proposed pilot study will test, not findings that have been measured.

5.1 Anticipated Impact on Interview Confidence

Previous AI-based mock interview studies have shown increases in student readiness and confidence after practicing with similar systems (Gomez et al., 2025). Since the proposed system

would have similar elements (adapting, generating questions and providing multi-level feedback), the proposed pilot study (Section 4) would be expected to see an increase in confidence in interviews reported by participating students as well, an assertion that still has to be proven.

5.2 Anticipated Value of Repeatable, Structured Practice

The system's provision of structured feedback on the three evaluation dimensions is intended to provide students with a consistent basis for self-directed improvement across sessions, addressing the repetition and consistency limitations of traditional coaching identified in Section 1.2. This design goal is consistent with previous systems finding that repeated, judgment-free AI practice can improve candidate readiness over time (Gomez et al., 2025; Amarasena et al., 2024).

5.3 Positioning Relative to Human-Led Coaching

Consistent with how others have framed the role of AI in interview preparation (Crutsinger & Herrera, 2022; Amarasena et al., 2024), I propose that the system be designed to support, rather than replace, human interview coaching — providing a means for generating a standardized, repeatable initial practice while reserving nuanced, subjective assessment (e.g., cultural context, non-verbal rapport) to humans, at least until the scores of the AI evaluator have been validated against human raters (Section 7).



6. LIMITATIONS

Several limitations should be acknowledged in the proposed system design and evaluation plan:

- **Assessment of soft skills and non-verbal cues.** While NLP and, where implemented, computer vision techniques can approximate confidence and engagement, they remain limited in capturing the full range of non-verbal communication, body language, and interpersonal rapport that human interviewers assess holistically (Jadhav et al., 2024).
- **Bias in NLP evaluation.** Language models and speech recognition systems can exhibit bias against non-native accents, regional English variants, or non-standard phrasing, potentially penalizing candidates unfairly rather than assessing genuine communicative competence — a concern that must be actively tested for and mitigated rather than assumed absent.
- **Risk of over-reliance and "gaming" the system.** Students may optimize responses toward patterns the AI evaluator rewards (e.g., specific keywords or phrasing) rather than developing genuine communicative competence, potentially inflating system-measured performance without corresponding real-world improvement.
- **Sample size and generalizability.** The proposed pilot study, limited to a single institution and a modest sample size, would have limited generalizability across engineering disciplines, institutions, or student populations with differing baseline English proficiency.
- **Absence of long-term outcome data.** The proposed evaluation plan measures confidence and evaluation scores only within a short study period and does not track whether improvements translate into actual placement or interview success, which would require longer-term, post-graduation follow-up.
- **Scope of evaluation criteria.** The system's three-dimensional evaluation framework (relevance, language proficiency, and confidence/delivery) may not fully capture domain-specific technical depth expected in core engineering interviews, which often require subject-matter expert evaluation beyond what general-purpose NLP/generative AI can reliably provide.
- **Absence of empirical validation.** As this paper presents a design and proposed evaluation methodology rather than completed empirical work, all anticipated benefits discussed in Section 5 remain hypotheses to be tested, not established findings.

7. CONCLUSION AND FUTURE WORK

This paper proposed an AI-driven mock interview system that integrated natural language processing (NLP)-based resume parsing and response evaluation with generative artificial intelligence (AI)-driven dynamic question generation to address engineering students' interview preparation needs. This paper draws on a growing body of literature on AI mock interview systems (Chou et al., 2022; Sharma et al., 2025; Singh et al., 2026) and NLP-based language assessment (Chapelle & Chung,

2010; Li, 2026; Zhang et al., 2026). Its contribution to the literature was an identification of the need to develop systems addressing the language-proficiency evaluation needs of engineering students, as interviews in their field tend to require higher levels of both technical and communicative competencies; this paper also proposed a mixed-methods evaluation design, including a single-group pre-test/post-test pilot study, to assess the effectiveness of such a system in subsequent work.

The proposed system, whose different aspects are described in this thesis, ranging from the resume parser to the question generator, through various methods of answering and scoring, and up to the final report creation, can be used as an effective, scalable, and affordable alternative to the traditional expensive and resource-limited coaching services, thus addressing the need identified in Section 2.3.

The most immediate direction for future work is to implement the proposed pilot study (Section 4) and test the anticipated results described in Section 5. Further studies should aim to evaluate how the scores provided by the AI evaluator relate to scores given by independent human interviewers for the same responses to establish validity and reliability; include video-based non-verbal analysis to complement the analysis of speech (Jadhav et al., 2024; Sharma et al., 2025); investigate the utility of the tool in larger studies at multiple institutions; address potential bias in the system against non-native English speakers and those with certain accents; and assess the long-term impact of using such tools, including whether the changes in the performance of the candidates lead to success in actual placement interviews. A promising direction for future work in this domain is to individualize the technical question stream, tailor it to each discipline, and therefore combine professional skills with technical expertise.

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