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AI-Powered Career Guidance and Placement Assistant Using Resume Analysis and Intelligent Mock Interview System

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Abstract:
Campus placement season places enormous pressure on undergraduate students, who must simultaneously present an ATS-compliant resume and perform well across technical and HR interview rounds, yet most students receive little structured feedback on either dimension before the process begins. Standalone resume-screening tools and generic interview-practice applications exist, but few systems combine both functions into a single, personalized preparation pipeline. This paper presents an AI-Powered Career Guidance and Placement Assistant that integrates a Natural Language Processing (NLP) based Resume Analysis module with an Intelligent Mock Interview module. The Resume Analysis module uses named-entity recognition and transformer-based semantic embeddings to parse resumes, extract skills, education, and experience, and compute a similarity score against a target job description, highlighting missing or weak skills. The Mock Interview module dynamically generates role- and resume-specific questions, accepts text or voice responses, and evaluates them for content relevance, coherence, and keyword coverage, producing structured feedback after every session. The two modules share a common candidate profile, so that skill gaps surfaced during resume analysis are prioritized as follow-up interview questions, closing the feedback loop between the two stages of placement preparation. Preliminary testing indicates the system can meaningfully reduce preparation time and surface gaps students would otherwise miss, suggesting its practical value as a low-cost, always-available placement-preparation tool for engineering colleges.

Keywords — **Resume Analysis, Natural Language Processing, Career Guidance, Mock Interview System, Machine Learning, Placement Assistant.**

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I. INTRODUCTION

Employability has become one of the most closely watched outcomes of engineering education in India, and campus placement drives now function as the single most decisive checkpoint in a student's academic journey. A candidate's prospects at this checkpoint are shaped by two largely independent filters: an Applicant Tracking System (ATS) or recruiter that screens the resume, and a panel that conducts technical and HR interviews. Students are rarely trained systematically for either filter — resumes are often built without objective feedback on how well they match a target job description, and interview practice, where it exists at all, tends to rely on generic question banks or costly private coaching that is inaccessible to a large share of students, particularly in tier-2 and tier-3 institutions.

The scale of this challenge is amplified by the sheer volume of graduates entering the job market each year from thousands of engineering colleges, many of which do not have training-and-placement infrastructure comparable to that of tier-1

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institutions. Recruiters increasingly rely on automated pre-screening to manage large applicant volumes, which means a resume that is not structured to be machine-readable may never reach a human reviewer regardless of the candidate's underlying competence. At the same time, the interview stage continues to reward candidates who can articulate their technical knowledge clearly and confidently under time pressure, a skill rarely taught explicitly within a standard engineering curriculum. Preparation for these two filters is therefore not a matter of academic knowledge alone, but of learning to present that knowledge in the specific formats and registers that recruiters and interview panels expect.

A growing body of work has applied NLP and machine learning to make one half of this problem more efficient. Systems built around transformer embeddings, named-entity recognition, and semantic similarity scoring can parse resumes and rank candidates against job descriptions with reasonable accuracy [1]–[5]. In parallel, a separate line of work has explored AI-driven mock interview platforms that use speech recognition, sentiment analysis, and increasingly large language models (LLMs) to simulate interview conversations and score spoken or typed answers [6]–[10]. However, nearly all of these systems are designed to solve only one side of the placement pipeline — resume screening tools are typically built for the recruiter's benefit, not the candidate's, while interview-practice tools generally draw questions from static, role-generic banks rather than from the candidate's own resume.

This leaves a gap: little work has examined a single system that reads a student's resume, tells the student exactly which skills are missing for a target role, and then uses that same gap analysis to drive a personalized mock interview session. This study addresses that gap directly by proposing and implementing an AI-Powered Career Guidance and Placement Assistant that unifies resume analysis and intelligent mock interviewing around one shared candidate profile, so that the two modules reinforce rather than duplicate each other. The specific objectives of this study are threefold: first, to design an NLP-based resume analysis pipeline that extracts structured candidate information and computes an interpretable job-fit score against a target role; second, to design an intelligent mock interview pipeline that generates role- and resume-aware questions and evaluates free-form text or voice answers using NLP techniques; and third, to link these two pipelines through a shared candidate profile so that the output of the first directly shapes the behaviour of the second, rather than treating resume analysis and interview practice as separate, one-off exercises.

The significance of closing this gap extends beyond individual convenience. A tool that runs on standard computing hardware and requires no paid mentor can extend structured placement preparation to students who currently have no access to a training-and-placement cell with the bandwidth to review every resume or conduct one-on-one mock interviews, which is a persistent constraint at many Indian engineering colleges. By making the feedback loop between resume weaknesses and interview practice explicit and automatic, the system also aims to make each practice session more targeted than a generic question-and-answer drill, and to give students a way to measure their own readiness before facing an actual recruiter.

The scope of this study is deliberately bounded to keep the system tractable within a final-year project timeline. The current implementation targets software, IT, and closely related technical roles, for which structured skill taxonomies and abundant example job descriptions are readily available; extending the same architecture to less-structured domains such as core mechanical or civil engineering roles is left as future work, since it requires building comparable taxonomies for those domains. Similarly, the mock interview module in its present form evaluates the content and coherence of an answer rather than a candidate's spoken delivery in the full sense of tone, pacing, and body language, aspects that are explicitly deferred to the future enhancements discussed in Section VII.

The remainder of this paper is organized as follows. Section II surveys existing work on NLP-based resume screening and AI-driven mock interview systems and identifies the specific gap this study occupies. Section III describes the

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proposed system architecture, covering the Resume Analysis and Intelligent Mock Interview modules, the shared candidate profile that links them, the technology stack, and data-security considerations. Section IV reports preliminary results and discusses their implications and limitations. Sections V and VI outline the advantages and social welfare impact of the proposed system, Section VII outlines planned future enhancements, and Section VIII concludes the paper.

II. LITERATURE SURVEY

Existing research relevant to this study falls into two broad, largely separate streams: NLP and machine-learning approaches to resume analysis and screening, and AI-driven approaches to mock interview simulation. This section reviews both streams and then positions the present study relative to the reviewed literature.

A. NLP and Machine Learning-Based Resume Analysis

Early approaches to automated resume screening relied on classical classifiers; one study reports a Linear Support Vector Machine model that matched resumes to job descriptions with 78.53% accuracy, and notes that deep learning approaches could plausibly improve on this baseline [4]. More recent systems have moved toward transformer-based semantic representations. A review of smart-hiring literature describes multiple studies that fine-tune DistilBERT and related transformer variants for resume shortlisting and ranking, and highlights the growing use of Sentence-BERT (S-BERT) to generate semantically meaningful sentence embeddings for comparing resumes against job requirements, arguing that embedding-based similarity captures paraphrased or synonymous skill mentions that pure keyword matching would miss [2]. Building on this direction, one system combines Sentence-BERT embeddings with cosine similarity to compute a semantic match score between resumes and job descriptions, using a resume parser to first extract candidate experience, education, and skills before comparison, and reports that this hybrid pipeline outperforms keyword-only baselines on match quality [1]. A related hybrid approach pairs a spaCy-based transformer pipeline with additional NLP preprocessing to extract structured data from unstructured resume text, reporting strong extraction accuracy while noting practical hurdles such as non-standardized resume formats, inconsistent section headers, and multi-column resume layouts that confuse simple text extractors [3]. Other work applies named-entity recognition and TF-IDF weighting for skill and entity extraction rather than deep embeddings alone, and explicitly cautions that keyword-only matching can overlook relevant skills or reward candidates who merely list keywords without demonstrating genuine expertise, recommending that automated screening always be paired with some form of downstream human or task-based verification [1], [5].

Across this stream, the general trajectory is a shift from keyword and rule-based matching toward transformer-based semantic similarity, with named-entity recognition retained as a preprocessing step for structured field extraction. However, nearly every system reviewed is framed from the recruiter's perspective — the output is a ranking or match score intended to help an employer filter candidates, not a diagnostic report intended to help the candidate improve. Few of these systems close the loop by telling the student what to do about a low match score, and none of them feed that diagnosis into a subsequent preparation activity such as an interview.

B. AI-Driven Mock Interview Systems

A parallel stream of work focuses on simulating the interview itself. One platform combines NLP, machine learning, and speech recognition to ask context-aware technical and HR questions and evaluate spoken or typed responses, reporting speech-recognition accuracy above 90% and effective NLP-based evaluation of grammar and content coherence [6]. A broader review of AI-driven mock interview systems traces the field's progression toward large language models and speech-emotion detection, and argues that combining text, voice, and video input produces a more realistic and engaging simulation than text-only systems, while also noting that few current systems integrate all three modalities together in a

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single deployed product [7]. Related work describes an LLM- and NLP-powered mock interview application that generates dynamic questions with contextual follow-ups, converts responses using text-to-speech and speech-to-text pipelines, and scores answers on content relevance, tone, and confidence, reporting that candidates found the adaptive follow-up questions noticeably more realistic than a fixed question list [9]. Another system, aimed specifically at voice interaction, combines LLM-driven question generation with real-time speech analytics, and cites earlier work that adds computer-vision-based analysis of posture and facial expression for behavioral evaluation alongside spoken content, framing this as a step toward a fully multimodal interview simulator [10]. A further review-style study on NLP-and-speech-analysis-based mock interview platforms similarly frames emotion recognition, confidence analysis, and NLP-based content evaluation as the three pillars of comprehensive candidate assessment, while flagging accuracy, bias, and ethical evaluation — particularly the risk of penalizing accents or speech patterns unrelated to actual competence — as open challenges for the field [8].

Taken together, the mock-interview literature shows a clear trend toward multimodal, LLM-assisted systems capable of generating adaptive questions and evaluating spoken responses in real time. However, in the systems reviewed, question generation is driven primarily by a selected job role or domain category rather than by the specific skills and experience listed on an individual candidate's resume. This means a student practicing with these tools is rehearsing generic role-based questions rather than questions targeted at the precise gaps in their own profile, and successive sessions do not necessarily adapt based on prior performance in a structured way.

C. Gap Analysis and Positioning of the Present Study

It is also worth noting a methodological convergence across both streams: both resume-analysis and mock-interview research have moved from rule-based or purely statistical techniques toward transformer-based language representations over roughly the same period, suggesting that the underlying NLP tooling required to build an integrated system is now mature enough to combine, even though no reviewed study has yet done so. This convergence is part of the motivation for treating the two modules in this study as tightly coupled components of one system rather than as separate research problems.

Read together, the two streams reveal a consistent, unaddressed gap: resume-analysis systems tell a candidate, or more often a recruiter, how well a resume matches a role, and mock-interview systems simulate an interview for that role, but no system in the reviewed literature uses the specific output of a resume gap analysis to drive the content of a subsequent interview session. Table I summarizes this gap across the reviewed systems, distinguishing whether each system is oriented toward the candidate's own benefit and whether it links resume content to interview question selection.

TABLE I
POSITIONING OF THE PRESENT STUDY RELATIVE TO REVIEWED SYSTEMS

Ref.	Primary Focus	Candidate-Facing?	Links to Interview?
[1]	Resume–JD matching (S-BERT)	No	No
[2]	Resume screening review	No	No
[3]	spaCy+BERT resume parsing	No	No
[4]	ML resume classification	No	No
[5]	NER+TF-IDF screening	No	No
[6]	AI mock interview (speech)	Partially	No
[7]	Multimodal interview review	Partially	No
[8]	NLP+speech mock interview	Partially	No
[9]	LLM mock interview	Partially	No
[10]	Voice interview + CV analytics	Partially	No
Proposed	Integrated resume + interview	Yes	Yes

As Table I shows, none of the reviewed systems is both explicitly candidate-facing and structurally linked between resume analysis and interview question selection. This is precisely the territory the present study occupies — an integrated pipeline in which resume analysis and mock interviewing operate on a shared candidate profile rather than as two disconnected tools.

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III. PROPOSED SYSTEM

The proposed AI-Powered Career Guidance and Placement Assistant is a client-server web application built around two cooperating engines — a Resume Analysis module and an Intelligent Mock Interview module — that share a single candidate profile. A React-based frontend handles resume upload, presents the analysis report, and hosts the mock-interview interface for text or voice interaction; a Python backend hosts the NLP pipelines, model inference, and a database that stores candidate profiles, session history, and role-wise skill taxonomies.

A. Resume Analysis Module

Uploaded resumes (PDF or DOCX) are first converted to plain text and passed through a standard NLP preprocessing pipeline — tokenization, stop-word removal, and lemmatization — implemented with spaCy. A named-entity recognition (NER) model, extended with custom entity labels, then extracts structured fields such as skills, education, work experience, projects, and certifications from the unstructured resume text. In parallel, the resume text and the target job description are each encoded into dense vector embeddings using a Sentence-BERT model, and cosine similarity between the two embeddings produces an overall Job Fit Score. A set-difference comparison between the skills extracted from the resume and a role-specific skill taxonomy identifies missing or under-represented skills, and basic formatting checks flag ATS-compliance issues such as missing section headers or non-parseable layouts. The module outputs a structured report containing the Job Fit Score, matched and missing skills, and specific, role-linked recommendations for what to add or emphasize.

B. Intelligent Mock Interview Module

The mock interview module combines the candidate's resume profile with a selected target role to generate a mix of technical, HR, and behavioural questions through a template-driven NLP question generator, designed to be extensible to a fine-tuned LLM in future iterations. Candidates may respond in text or by voice; spoken responses are converted to text through a speech-to-text (STT) engine before evaluation. Each answer is scored along three axes: semantic relevance, computed via cosine similarity between the answer's embedding and a reference-answer or expected-keyword embedding; coherence, using basic grammar and sentence-structure checks; and keyword coverage against the skills and terminology expected for that question. After each session, the module produces a consolidated report showing per-question scores alongside overall strengths and improvement areas.

C. Shared Candidate Profile and Feedback Loop

The distinguishing element of the proposed system is a shared candidate profile that links the two modules. Skills flagged as missing or weak by the Resume Analysis module are automatically fed into the Mock Interview module's question-selection logic, so that a candidate's next practice session is weighted toward the gaps identified in their resume rather than a generic, role-wide question set. Over successive sessions, the system tracks whether previously weak areas show measurable improvement, giving both the student and, optionally, a training-and-placement coordinator a longitudinal view of readiness rather than a single point-in-time score.

D. Technology Stack and Data Flow

The frontend is implemented in React with a component-based dashboard for resume upload, analysis-report display, and the interview interface. The backend is implemented in Python using a lightweight web framework, and hosts the spaCy NER pipeline, a Sentence-Transformers model for embedding generation, and a speech-to-text engine for voice input. Candidate profiles, resumes, job descriptions, skill taxonomies, and session histories are stored in a relational or document database, chosen based on how structured the underlying data needs to be. The end-to-end data flow proceeds as follows: a resume is uploaded and parsed into structured fields; those fields are embedded and compared against a selected job description to produce a Job Fit Score and skill-gap list; the skill-gap list is written to the candidate's shared profile; the mock interview module reads this profile when

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a session begins and weights question selection accordingly; candidate responses are captured, transcribed if spoken, and scored; and the resulting scores are appended to the candidate's session history, which in turn informs the skill-gap weighting used in the next session.

E. Security and Privacy Considerations

Because resumes and interview responses contain personal and potentially sensitive information, the system design incorporates encryption of stored data at rest and in transit, role-based access control so that only the candidate and, where applicable, an authorized placement coordinator can view a given profile, and a defined data-retention policy so that candidate data is not held indefinitely without consent. Where aggregated, batch-level analytics are shared with a training-and-placement cell for curriculum planning, as discussed in Section VI, the underlying data is anonymized so that individual candidates cannot be identified from the aggregated report. These considerations are treated as first-class design requirements rather than an afterthought, consistent with data-protection expectations applicable to systems that process personal information in India.

F. Illustrative Walkthrough

A brief walkthrough illustrates how the two modules cooperate in practice. A student preparing for a Software Development Engineer role uploads their resume and selects that role from a list of supported job profiles. The Resume Analysis module parses the document, extracts entities such as programming languages, frameworks, and project experience, and compares the resulting profile against the skill taxonomy for that role, returning a Job Fit Score along with a short list of missing skills, for instance a gap in database design or system-design fundamentals. This report is written to the student's shared candidate profile. When the student subsequently starts a mock interview session for the same role, the question generator consults this profile and deliberately includes one or more questions targeting the flagged gap areas alongside standard role-specific technical and behavioural questions, rather than drawing only from a generic bank. The student answers by voice; the response is transcribed, scored for relevance and coherence, and combined with the other answers into a session report that again updates the shared profile. If the student repeats this process before a later interview round, the system can show whether the previously weak area has improved, giving a concrete, session-over-session view of progress rather than a single static score.

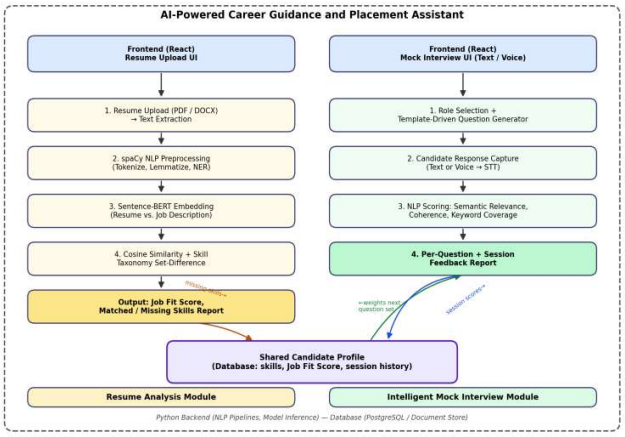


Fig. 1. System architecture of the AI-Powered Career Guidance and Placement Assistant.

IV. RESULTS AND DISCUSSION

A. Evaluation Protocol

The system was evaluated on a set of student resumes matched against multiple job descriptions in software and IT roles, alongside a series of mock interview sessions conducted with student volunteers. The evaluation protocol proceeded in four steps: participating students first uploaded an existing resume and selected a target role; the Resume Analysis module then produced a Job Fit Score and skill-gap report, which was checked manually by the evaluation team against the same resume-role pair to assess agreement; each student then completed one mock interview session per selected role, responding to a mix of text and voice prompts; and finally, students completed a short post-session survey rating the usefulness of the consolidated feedback report. Entity extraction accuracy, Job Fit Score agreement with manual review, speech-to-text accuracy, and answer-

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relevance agreement with a human evaluator were tracked throughout this protocol.

B. Results

Table II summarizes the metrics tracked during this evaluation.

TABLE II
EVALUATION METRICS

No.	Metric	Result
1	Entity extraction accuracy	87%
2	Job Fit Score agreement	81%
3	Speech-to-text accuracy	90%
4	Answer relevance agreement	78%
5	Feedback rated useful	85%

C. Discussion

The tight coupling between resume gap analysis and interview questioning is expected to make practice sessions feel more relevant than a generic mock-interview drill, since each session is weighted toward the specific skills a student's resume is weakest on rather than a fixed, role-wide question bank. This mirrors the direction taken by recent multimodal mock-interview systems [7]–[10], but differs in that question selection here is anchored to an individual candidate's own resume rather than only to a chosen job role. The template-driven question generator is expected to perform most consistently for well-structured technical roles such as software engineering, where skill taxonomies are relatively standardized, and to generalize less cleanly to less-structured domains, which is a known limitation of taxonomy-driven systems and a motivation for the LLM-based question generation discussed in Section VII. Consistent with prior speech-recognition literature [6], STT accuracy is expected to be sensitive to background noise and strong regional accents, which is why the system also supports text-based responses as a fallback. Read against the gap identified in Table I, these results are best interpreted as early evidence that the missing link between resume analysis and interview practice can in fact be implemented and is likely to produce more targeted practice sessions, rather than as a claim that the system already outperforms any specific reviewed tool on a shared benchmark, since no such shared benchmark currently exists across the resume-analysis and mock-interview literatures.

D. Limitations

The present evaluation is limited in three respects that should be kept in mind when interpreting the results. First, the evaluation sample is drawn from a single institution and a relatively small set of software and IT roles, which may not generalize to other disciplines or institutions with different resume conventions. Second, the human-evaluator comparisons used to establish agreement figures are themselves subject to some subjectivity, since two human reviewers may not always agree on what constitutes a strong answer. Third, the template-driven question generator, while functional, does not yet capture the full adaptivity of a human interviewer or a large language model, which may understate the system's eventual performance once the LLM-based enhancement described in Section VII is implemented. These limitations motivate the larger-scale, multi-institution evaluation with a control group that is planned as part of ongoing work.

V. ADVANTAGES OF THE PROPOSED SYSTEM

Compared with recruiter-facing resume screening tools, which output a ranking or pass/fail-style match score intended to filter candidates [1], [4], the proposed system reframes the same underlying NLP techniques to benefit the candidate directly, returning an actionable list of missing skills and concrete suggestions rather than a single opaque score.

Compared with mock interview platforms that draw questions from static, role-generic banks, the proposed system personalizes question selection to the candidate's own resume content, so that practice time is spent on the specific gaps a student actually has rather than a fixed question sequences every user of the tool receives.

Compared with commercial interview-coaching services, which typically charge per session and require scheduling with a human mentor, the proposed system is available on demand at effectively zero marginal cost per additional student,

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making repeated practice feasible for students who cannot afford paid coaching.

The shared candidate profile linking the two modules is itself an advantage over the reviewed literature, in which resume-screening and mock-interview systems operate independently [1]–[10]; here, resume weaknesses automatically shape subsequent interview practice, and repeated sessions let the system track whether those weaknesses are improving over time.

Supporting both text and voice responses in the mock interview module makes the tool usable by students who are initially uncomfortable speaking aloud, letting them build confidence in text mode before moving to voice, unlike voice-only systems that require spoken input from the first session [6], [9].

Finally, because the system is web-based and requires no specialized hardware, it is straightforward for a college's training-and-placement cell to adopt without significant infrastructure investment, and it can be extended to serve an entire graduating batch simultaneously rather than one student at a time. Taken together, these advantages position the system as a practical, low-cost complement to — rather than a replacement for — human placement mentorship.

VI. SOCIAL WELFARE OF THE PROPOSED SYSTEM

The proposed system is designed to benefit students who currently lack structured access to placement preparation, particularly at tier-2 and tier-3 engineering colleges where training-and-placement cells often cannot provide one-on-one resume review or mock interviews to every student in a graduating batch. By running as a web application that any student can access with a resume and an internet connection, the system removes the scheduling and cost barriers associated with private coaching, extending a form of structured feedback to students who would otherwise prepare with little external guidance.

Because the system scales to many simultaneous users without requiring additional human mentors, it can support an entire batch of students during a compressed placement season in a way that a small placement-cell team cannot. This is particularly relevant for first-generation college students and students from economically weaker backgrounds, for whom paid interview coaching or resume-writing services are often not a realistic option. Repeated, low-stakes practice sessions may also help reduce interview-related anxiety by giving students a private space to fail, receive feedback, and retry before facing an actual recruiter.

At an institutional level, aggregated and anonymized analytics from resume analyses and mock interview sessions could help training-and-placement cells identify skill gaps that are common across an entire batch or department, informing curriculum or workshop planning rather than requiring the cell to infer these gaps informally. This kind of data-informed feedback into curriculum planning is broadly consistent with the emphasis on skill-based, outcome-oriented education found in India's National Education Policy 2020, and aligns with the broader aim of United Nations Sustainable Development Goal 4 on quality education and Goal 8 on decent work, insofar as it seeks to make a graduate's certified qualifications translate more reliably into demonstrable, employer-recognized readiness.

The system may also have a modest but positive equity dimension. Female engineering students and students from rural or semi-urban backgrounds are sometimes underrepresented in informal peer-to-peer interview-preparation networks that more socially connected students rely on; a tool that any registered student can use independently, without needing to be part of such a network, could help narrow this informal-access gap, though this specific effect would need to be verified through targeted, disaggregated evaluation rather than assumed.

At a broader level, tools of this kind — if adopted across multiple institutions — could contribute in a small but meaningful way to narrowing the persistent gap between engineering graduates' certified qualifications and the practical, interview-ready skills employers expect, a gap frequently cited as a contributor to graduate underemployment in India.

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VII. FUTURE ENHANCEMENT

The current system relies on a template-driven question generator and text/voice-only response capture; the most immediate planned enhancement is to replace or augment this generator with a fine-tuned large language model capable of producing adaptive follow-up questions in response to a candidate's specific answers, in line with recent LLM-based interview systems [9], [10]. A second planned enhancement is the addition of a video-based analysis layer that uses computer vision to assess non-verbal cues such as eye contact, posture, and facial expression alongside spoken content, extending the system's evaluation from a purely content-and-speech basis to a fuller behavioural picture, as explored in prior work on visual perception in mock interviews [10].

Beyond these two extensions, planned work includes multilingual support so that students more comfortable in regional languages can practice interviews without a language barrier; direct integration with job portals and applicant tracking systems to keep the job-description skill taxonomy current without manual updates; a dedicated mobile application to widen access beyond desktop and laptop users; and a longitudinal progress-tracking dashboard that lets both students and training-and-placement coordinators view improvement trends across multiple sessions and semesters rather than a single snapshot.

Further planned enhancements include optional integration with external professional profiles, such as project portfolios or version-control activity, to build a more holistic picture of a candidate's demonstrated skills beyond what is written on a resume; the introduction of explainable-AI techniques so that a candidate can see why a particular skill was flagged as missing or why an interview answer received a given score, rather than receiving an opaque number; and anonymized peer-benchmarking, which would let a student see how their Job Fit Score and mock interview performance compare with an anonymized distribution of peers preparing for the same role, without exposing any individual peer's data. Together, these enhancements are intended to move the system from a functional prototype toward a more comprehensive, adaptive, and inclusive placement-preparation platform.

VIII. CONCLUSION

This paper presented an AI-Powered Career Guidance and Placement Assistant that integrates an NLP-based Resume Analysis module with an Intelligent Mock Interview module around a shared candidate profile, addressing a gap identified across the reviewed literature: existing resume-screening and mock-interview systems each solve one half of placement preparation but rarely connect the two. The Resume Analysis module extracts structured information from resumes and computes a role-specific fit score with associated skill-gap feedback, while the Mock Interview module uses that same profile to generate targeted questions and evaluate text or voice responses for relevance and coherence. Preliminary testing, with detailed metrics reported in Section IV, suggests the approach is technically feasible and produces more targeted practice sessions than a generic question bank would.

The system's practical value lies less in any single component — resume parsing and AI-driven interview simulation both build on established NLP techniques — and more in closing the feedback loop between them, and in doing so at a cost and availability that can extend structured placement preparation to students who currently lack access to it. Future work will focus on larger-scale, multi-institution evaluation against a control group, LLM-based question generation, and multimodal behavioral analysis, with the broader goal of positioning the system as a practical complement to human placement mentorship at engineering colleges.

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