IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 18, April 2026
Impact Factor: 8.2

AI-Driven Campus Placement Readiness Analyzer

Swaraj Memane[1], Swarali Memane[2], Sangram Sonwane[3], Prof. Neha Chaube[4]
[123]Student, School of Computing, MIT ADT University, Pune, Maharashtra, India
[4]Assistant Professor, School of Computing, MIT ADT University, Pune, Maharashtra, India
swarajmemane13@gmail.com, swaralimemane13@gmail.com, sangramsss2005@gmail.com
neha.chaube@mituniversity.edu.in

Abstract: *Securing a campus placement remains one of the most demanding milestones for engineering and management graduates. A principal contributor to placement failure is the absence of a unified, intelligent platform capable of evaluating student preparedness across multiple competency dimensions simultaneously. This paper presents an AI-Driven Campus Placement Readiness Analyzer—a web-based intelligent system that combines Natural Language Processing (NLP) for automated resume evaluation with an adaptive Machine Learning (ML) skill assessment engine. The system derives a composite Placement Readiness Index (PRI) by integrating resume quality metrics with domain-specific technical proficiency scores, subsequently generating personalized gap analyses and structured improvement roadmaps for individual students. The proposed architecture was validated through a pilot study involving 87 final-year engineering students; results indicate noticeable improvements in student self-awareness and targeted preparation efficiency. The platform is institution-agnostic, mentor-accessible, and designed for scalable deployment across diverse academic environments..*

Keywords: *Placement Readiness; Resume Parsing; Skill Assessment; NLP; Machine Learning; Adaptive Testing; Gap Analysis; Placement Readiness Index; Student Evaluation; Career Guidance*

I. INTRODUCTION

The transition from academic study to professional employment represents a defining juncture in every student's career trajectory. Campus placement drives serve as the primary conduit for this transition within the Indian higher education landscape; yet a substantial proportion of students consistently underperform during recruitment events. Empirical evidence suggests that inadequate preparation—rather than an inherent lack of capability—constitutes the foremost cause of placement failure.Students often spend time on coding practice or resume updates without clearly understanding how these efforts align with the expectation of modern recruiters.

Contemporary campus recruiters evaluate candidates across several distinct dimensions: technical proficiency, resume presentation quality, aptitude performance, and communication ability. Currently, there is no single platform that effectively combines all these evaluation aspects into one unified system.

AI driven approaches provide a scalable and efficient way to address this challenge . By leveraging NLP to interpret resume content and ML models to quantify technical readiness, an intelligent system can provide comprehensive, personalized, and unbiased feedback at a scale that human mentors cannot realistically match.

A. Problem Statement

Students preparing for placements lack a dependable and unified system to evaluate their readiness.Preparation is mostly self driven, which often leads to uneven skill development and uneven gaps. Resume quality is frequently suboptimal due to the absence of professional feedback, while available skill assessments tend to be either excessively narrow or insufficiently targeted.

Furthermore, placement coordinators and faculty mentors lack data-driven dashboards to identify which students require urgent intervention. The proposed system directly addresses this gap by offering a unified evaluation platform

DOI: 10.48175/IJARSCT-34352

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 18, April 2026
Impact Factor: 8.2

that assesses both resume quality and technical skill readiness, computes an integrated readiness score, and generates a personalized improvement plan for each student.

B. Review of Existing Work

There has been significant growth in AI-based career guidance research in recent years. Resume parsing tools built on spaCy and NLTK have demonstrated high accuracy in extracting structured information from unstructured documents. Bharadwaj and Bhatia [1] established the effectiveness of keyword-based feature extraction combined with gradient boosting classifiers for automated candidate ranking.

Adaptive assessment systems based on Iteam Response Theory (IRT) have been widely used in standardized evaluations to improve accuracy and measurement efficiently. Goel et al. [2] demonstrated that adaptive assessments yield significantly more reliable proficiency estimates relative to static tests of equivalent length. The proposed approach improves existing methods by combining both techniques into unified system.

C. Research Objectives

This research pursues the following specific objectives:

- Design an NLP pipeline capable of parsing student resumes and evaluating them against recruiter-aligned quality criteria, including section completeness, keyword relevance, quantifiable impact statements, and formatting standards.
- Develop an adaptive skill assessment engine encompassing Data Structures and Algorithms, Database Management Systems (DBMS), Operating Systems, Computer Networks, and Object-Oriented Programming.
- Engineer a Placement Readiness Index (PRI) scoring model that integrates resume quality scores and skill proficiency scores using a validated weighting framework derived from industry recruiter feedback.
- Construct a personalized feedback and recommendation engine that maps each student's identified deficiencies to curated learning resources and structured improvement tasks.
- Develop a mentor-accessible analytics dashboard enabling placement coordinators to monitor cohort-level readiness and proactively identify high-risk students.

II. SYSTEM ARCHITECTURE AND DESIGN

The Placement Readiness Analyzer is structured around a layered architecture comprising five interconnected modules. Each module is independently deployable and communicates through a RESTful API layer, enabling flexible integration with existing institutional Learning Management Systems (LMS) or placement portals.

A. Data Input Layer

The input layer accepts two primary data streams: a resume document in PDF or DOCX format, and student responses to an adaptive skill assessment administered via the system's browser-based interface. Students may optionally specify their target job domain and preferred company type, enabling domain-specific customization of both assessment and feedback.

B. Preprocessing and Parsing Unit

Uploaded resumes are processed through a multi-stage NLP pipeline. Text extraction accommodates both DOCX and PDF formats using Apache PDFBox and the python-docx library. The extracted text is segmented into logical sections using pattern-matching heuristics combined with a trained section classifier. Named Entity Recognition (NER) subsequently identifies candidate names, academic institutions, prior employers, dates of activity, and technical skills.

C. Resume Analysis Module

The resume analysis module evaluates the structured candidate profile against a multi-criteria quality rubric that encompasses: the presence and completeness of essential resume sections; keyword alignment computed via TF-IDF similarity against a domain-specific corpus; action verb density; density of quantifiable impact statements; and overall formatting consistency. A weighted aggregate Resume Quality Score (RQS) is computed on a normalized 0–100 scale.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 18, April 2026
Impact Factor: 8.2

D. Skill Assessment Module

The skill assessment module administers an adaptive technical test powered by an IRT engine. The question bank contains more than 600 validated items distributed across five core engineering domains, with item difficulty calibrated using the three-parameter logistic (3PL) IRT model. The adaptive algorithm selects the next item by maximizing Fisher Information at the current proficiency estimate, yielding accurate proficiency scores in 20–30 items compared to 60–80 items required by conventional static tests.

E. Scoring Engine and PRI Computation

The Placement Readiness Index (PRI) is computed as a weighted linear combination of the Resume Quality Score (RQS) and the Skill Proficiency Score (SPS):

$$\mathbf{PRI = 0.40 \times RQS + 0.60 \times SPS} \quad (1)$$

The weights were derived empirically through regression analysis applied to historical placement outcome data spanning three academic cohorts. The PRI is expressed on a 0–100 scale and mapped to four descriptive readiness bands: Beginner (0–40), Developing (41–60), Competent (61–75), and Ready (76–100).

F. Feedback and Recommendation Engine

Based on criterion-level diagnostic scores, the recommendation engine maps each identified deficiency to a curated set of improvement actions. Resume-related deficiencies are linked to rewriting guidelines and professional sample templates. Skill gaps are associated with topic-specific study resources, graded practice problem sets, and estimated study timelines. Student- and mentor-facing reports are generated in fluent natural language through a template-driven NLG module.

III. CONCEPTS AND METHODOLOGY

The system is based on three main conceptual components: intelligent document understanding, adaptive knowledge measurement, and evidence-based gap analysis. Together, these components enable a holistic evaluation that approximates the multi-dimensional judgment of experienced placement professionals, while delivering the consistency and throughput that only automated systems can sustain.

A. NLP-Based Resume Intelligence

Resume intelligence is performed using a combination of rule-based and statistical NLP methods. Section detection relies on a hybrid classifier trained on 1,200 manually annotated resumes. Keyword extraction employs a domain-adapted TF-IDF model supplemented by a curated technical skills ontology encompassing 850 terms across twelve engineering domains. Semantic similarity is computed using cosine distance over SBERT sentence-transformer embeddings [3], enabling nuanced matching that extends well beyond exact keyword overlap.

B. Adaptive Skill Assessment

The adaptive testing modules follows principal inspired by the catR framework and is implemented in Python for seamless integration. Each student's initial proficiency estimate θ is set at the population mean and updated after every response using maximum likelihood estimation. The subsequent item is selected by maximizing Fisher Information at the current θ estimate [4]. Assessment terminates when the standard error of measurement falls below a predefined threshold or when the maximum item limit is reached, reliably yielding accurate proficiency estimates within 20–30 items.

C. PRI Validation

The PRI weighting model was validated using binary logistic regression applied to placement outcome data from 412 students collected over three academic years. The regression model attained an Area Under the ROC Curve (AUC) of 0.83 on the hold-out test set, confirming strong predictive validity. Calibration analysis further established that PRI values above 65 correspond to a placement success probability exceeding 78%, providing a meaningful and operationally actionable performance threshold.

D. System Implementation

The platform is realized as a full-stack web application. The backend is implemented in Python using the FastAPI framework, with spaCy 3.5 and Hugging Face Transformers [5] powering the NLP components. The adaptive testing engine is implemented in pure Python utilizing NumPy. The frontend is developed in ReactJS and communicates with the backend exclusively via REST APIs. PostgreSQL serves as the primary relational data store. The entire application is containerized using Docker and deployed on cloud infrastructure to support horizontal scalability.

IV. RESULTS AND DISCUSSION

A pilot evaluation was conducted with 87 final-year B.Tech students drawn from three disciplines—Computer Science, Information Technology, and Electronics Engineering—at MIT ADT University. Participants engaged with the system over a four-week period immediately preceding scheduled on-campus placement drives. Key observations are presented below and summarized in Table I.

1) Resume Quality Improvement: The mean RQS improved from 51.3 at baseline to 68.9 following the intervention period, representing a 34.3% average improvement across the cohort.

2) Skill Gap Identification: A total of 92% of participants reported that the system surfaced at least one significant skill deficiency of which they had previously been unaware. Database Management Systems (DBMS) and Computer Networks were the most frequently flagged weak areas.

3) Placement Outcome Correlation: Students who attained a PRI exceeding 65 achieved a campus placement rate of 81%, compared to a placement rate of 43% among students whose PRI fell below 50, demonstrating a strong predictive relationship between PRI and recruitment success.

4) Student Satisfaction: Of the participating students, 89% characterized the system-generated feedback as directly actionable, and 84% reported a measurable increase in overall confidence in advance of placement interviews.

TABLE I: *Summary of Pilot Study Results*

Metric	Pre-Intervention	Post-Intervention
Avg. Resume Quality Score (RQS)	51.3	68.9 (+34.3%)
Placement Rate (PRI > 65)	—	81%
Placement Rate (PRI < 50)	—	43%
Students Finding Feedback Actionable	—	89%
Reported Improvement in Interview Confidence	—	84%

V. FUTURE WORK

Although the current implementation demonstrates strong foundational performance, several directions merit investigation in subsequent development phases.

First, integrating a speech-based mock interview module powered by automatic speech recognition (ASR) and multi-dimensional sentiment analysis would extend the evaluation framework to verbal communication and structured reasoning—critical competencies assessed during HR interview rounds.

Second, real-time labor market integration via job portal APIs would enable automatic updating of domain-specific keyword corpora and skill benchmarks, ensuring that students consistently prepare against current, industry-relevant standards rather than static historical data.

Third, a multi-agent conversational AI environment for group discussion simulation would allow the system to assess collaborative skills, leadership behavior, and active listening competence—dimensions currently beyond the scope of individual-focused assessment.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 18, April 2026
Impact Factor: 8.2

Fourth, adoption of federated learning would enable continuous model refinement without centralizing sensitive student records [6]. Each institutional deployment would train locally and contribute only anonymized gradient updates, achieving performance improvement while fully preserving student privacy.

Finally, longitudinal tracking across academic semesters would enable the system to model individual student growth trajectories and generate predictive alerts for students exhibiting early indicators of placement risk, thereby facilitating timely and targeted mentor intervention.

VI. CONCLUSION

The study presented the design, development and initial validation of an AI-Driven Campus Placement Readiness Analyzer. The system addresses a well-documented deficiency in student placement preparation by integrating NLP-based resume analysis with adaptive ML-driven skill assessment into a unified, data-driven evaluation platform.

The proposed Placement Readiness Index furnishes a holistic, empirically validated composite metric that reliably reflects a student's overall preparedness for campus recruitment. Findings from the pilot study confirm that the system delivers actionable diagnostic insights that translate into statistically meaningful improvements in both resume quality and actual placement outcomes.

As placement environment become more competitive, intelligent preparation support systems like this are expected to become essential institutional infrastructure. With continued development in soft-skill assessment, real-time industry alignment, and federated privacy-preserving learning, the proposed platform holds considerable potential to advance placement equity and improve outcomes across diverse student populations.

REFERENCES

[1] A. Bharadwaj and M. Bhatia, "Resume analysis and candidate ranking using NLP and machine learning: A systematic review," Int. J. Adv. Comput. Sci. Appl., vol. 11, no. 5, pp. 248–255, 2020.

[2] S. Goel, A. Tyagi, and R. Sharma, "Adaptive skill assessment for engineering students using item response theory," J. Educ. Technol. Syst., vol. 47, no. 3, pp. 312–334, 2019.

[3] N. Reimers and I. Gurevych, "Sentence-BERT: Sentence embeddings using Siamese BERT-networks," in Proc. 2019 Conf. Empirical Methods Natural Language Process. (EMNLP-IJCNLP), Hong Kong, 2019. [Online]. Available: https://arxiv.org/abs/1908.10084

[4] F. B. Baker and S. H. Kim, Item Response Theory: Parameter Estimation Techniques, 2nd ed. New York, NY, USA: Marcel Dekker, 2004.

[5] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in Proc. 2019 Conf. North American Chapter Assoc. Comput. Linguistics: Human Language Technol. (NAACL-HLT), Minneapolis, MN, USA, 2019, pp. 4171–4186.

[6] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," ACM Trans. Intell. Syst. Technol., vol. 10, no. 2, pp. 1–19, Jan. 2019, doi: 10.1145/3298981.

[7] C. D. Manning, P. Raghavan, and H. Schütze, Introduction to Information Retrieval. Cambridge, U.K.: Cambridge Univ. Press, 2008.

[8] M. Chen, Y. Hao, K. Hwang, L. Wang, and L. Wang, "Disease prediction by machine learning over big data from healthcare communities," IEEE Access, vol. 5, pp. 8869–8879, 2017, doi: 10.1109/ACCESS.2017.2694446.