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Artificial Intelligence (AI)-Based Resume Analysis and Job Matching

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ABSTRACT

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The transition from academic education to professional employment requires students to communicate technical skills, projects, certifications, education, and experience in a form that is relevant to a specific job. This paper presents an AI-based resume analysis and job-matching approach designed to provide understandable, job-specific feedback to engineering students. The system accepts a PDF resume and a target job description, extracts resume text using pdfplumber with pypdf as a fallback, and submits the normalized information to an AI analysis component. The revised methodology makes the compatibility score more transparent by interpreting it through three dimensions: required-skill coverage, semantic relevance between resume evidence and job requirements, and evidence strength from projects, education, and experience. The system returns four structured outputs: an ATS-style compatibility score, matched skills, missing or insufficiently represented skills, and actionable recommendations. Unlike a commercial Applicant Tracking System, the score is explicitly positioned as a decision-support estimate rather than an employer-generated recruitment score. Implementation-level testing on three sample technical cases produced compatibility scores of 78%, 64%, and 71%, with a mean of 71.0%. These values demonstrate functional variation across job-specific inputs but are not treated as predictive accuracy because the current study does not use a sufficiently large labeled benchmark. A literature-grounded comparison further shows that existing approaches emphasize resume information extraction, skill taxonomy alignment, deep-learning recommendation, or job recommendation, whereas the proposed system integrates these ideas into a student-facing feedback workflow. The paper also identifies limitations related to dataset size, PDF extraction, AI variability, fairness, and external validation, and defines a future research plan involving a larger annotated benchmark, human agreement analysis, taxonomy-based skill normalization, and systematic evaluation against baseline matching methods.

1. Introduction

Engineering students frequently possess relevant technical knowledge but may find it difficult to express that knowledge in a resume that is aligned with a particular job description. A resume may include

programming languages, frameworks, academic projects, internships, certifications, coursework, and extracurricular achievements, while a job description may describe requirements using different terminology. This vocabulary and representation gap creates a practical need for tools that can compare the two documents and provide explanations rather than only a numerical result.

Automated recruitment has increased the importance of resume parsing, skill extraction, semantic matching, and recommendation. Recent research has explored deep-learning job recommendation, resume information extraction, taxonomy-driven skill extraction, and transformer-based matching. For example, deep neural recommendation models have been developed for resume recommendation, while recent NLP-for-HR research has examined skill extraction and classification from job postings and the use of large language models for complex skill mentions [1], [5], [6], [7].

Resume documents are difficult to process because their layouts, sections, terminology, and formats vary substantially. End-to-end resume extraction frameworks have therefore used combinations of information extraction, named-entity recognition, linguistic patterns, and machine-learning methods [8], [9], [10]. Skill extraction is similarly challenging because hard and soft skills can appear in different linguistic forms and because a single concept can be represented by synonyms or related terms [7], [11].

Recent work has also moved from simple keyword matching toward semantic and taxonomy-aware matching. ESCO-based approaches, multilingual skill extraction, and O*NET-based transformer matching demonstrate the value of standardized skill representations and semantic similarity [4], [12], [13]. At the same time, AI-assisted recruitment raises fairness and governance concerns, especially when automated systems influence candidate screening [14], [15], [16]. These concerns motivate a design in which the proposed system is a student decision-support tool rather than an autonomous hiring mechanism.

The present study focuses on the resume-analysis component of the AI-Powered Smart Campus & Career Hub. The system compares a student's resume with a selected job description and generates four outputs: compatibility estimation, matched skills, missing or insufficiently represented skills, and recommendations. The central contribution is the integration of these outputs into a single understandable workflow for engineering students. The revised paper also formalizes the interpretation of the compatibility score, adds a literature-grounded comparison, clarifies the evaluation scope, and strengthens the conclusion and future research plan.

1.1 Research Objectives

- 1) Extract usable textual information from heterogeneous PDF resumes.
- 2) Compare resume evidence with requirements in a target job description using AI-based semantic analysis.
- 3) Provide a transparent compatibility estimate rather than presenting the output as a commercial ATS score.
- 4) Identify matched skills and missing or insufficiently represented skills.
- 5) Generate actionable recommendations for improving a job-specific resume.
- 6) Evaluate functional behavior on sample technical cases and position the findings correctly within the limits of the current study.

1.2 Contributions

The proposed work integrates resume parsing, job-specific semantic analysis, skill-gap identification, and recommendations in one student-facing workflow. The revised methodology makes the compatibility estimate interpretable through explicit components instead of treating the score as an unexplained AI output. The paper provides a capability-level comparison with representative recent approaches and separates literature-reported benchmark metrics from the present implementation-level sample scores. The study explicitly addresses the difference between a missing skill and a missing resume representation, reducing the risk of over-interpreting automated skill-gap outputs.

Figure 1 presents the conceptual framework of the proposed system. The framework takes two inputs: the student's resume in PDF format (Input A) and the job description of the target position (Input B). Both inputs pass to the document processing and normalization stage, which extracts the resume text and prepares it, together with the job description, for analysis. The prepared inputs are then compared in the AI-based comparative analysis stage, which judges the resume against the role-specific requirements and summarizes

the result as the composite compatibility score C defined in Section 3.3, built from required-skill coverage (S), semantic relevance (M), and evidence strength (E). The analysis produces four structured outputs: the compatibility score, the matched skills, the missing or insufficiently represented skills, and actionable recommendations. Finally, the student reviews these findings and revises the resume, so the framework supports a human decision rather than replacing it. The individual stages of Figure 1 are detailed in Section 3 and Figure 2.

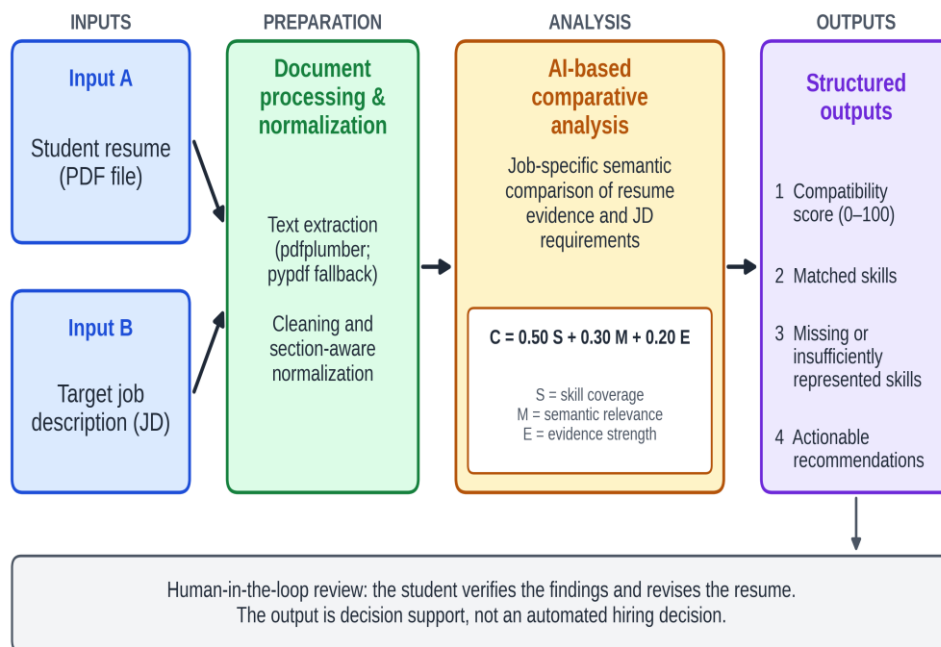


Fig. 1. Conceptual framework of the proposed AI-based resume analysis and job matching system.

2. Literature Review

Resume analysis and job matching are closely related but distinct tasks. Resume information extraction focuses on converting an unstructured candidate document into structured entities such as skills, education, roles, projects, and experience. Palshikar et al. developed RINX as an end-to-end resume information and knowledge extraction system and highlighted the substantial structural variation found across resumes [10]. Barducci et al. similarly described an end-to-end framework for extracting information from Italian resumes using named-entity recognition and semantically consistent document segments [9].

Skill extraction has become a central problem in computational job-market analysis. Senger et al. surveyed deep-learning approaches, datasets, and terminology for skill extraction and classification from job postings [1]. Wings et al. investigated context-aware extraction of hard and soft skills using BERT-based representations and linguistic features [11]. Gnehm et al. incorporated the ESCO ontology into skill requirement extraction and reported a mean average precision of 0.969 at the skill-class level in their evaluation setting [7]. These studies indicate that matching benefits from contextual representations rather than literal keyword occurrence alone.

Large language models have created another direction for skill extraction. Nguyen et al. investigated in-context learning for skill extraction and reported that LLMs can handle syntactically complex skill mentions even when traditional supervised models remain competitive on overall performance [6]. Magron et al. introduced JobScape and SkillsScape for synthetic job-posting generation and skill-to-taxonomy matching [2]. Kavas et al. proposed multilingual skill extraction and knowledge-graph alignment using ESCO labels [4]. ESCOX further demonstrates the practical use of LLMs and embeddings for taxonomy-aligned skill and occupation extraction [3]. On the matching side, Huang et al. proposed AIRANN, an attentive deep-learning resume recommendation model that combines textual and non-textual features and uses implicit relationships between resumes [5]. Other work has investigated heterogeneous graph convolutional networks and recurrent

neural networks for job recommendation [17], [18]. Alonso et al. combined transformer-based semantic similarity with O*NET entities for resume-job matching and skill recommendation [12]. These approaches demonstrate that modern matching systems can move beyond simple keyword overlap.

Research also emphasizes that recruitment AI should be treated cautiously. Hunkenschroer and Luetge reviewed ethical issues associated with AI-enabled recruitment and selection [14]. Drage and Mackereth examined claims around AI-driven recruitment and the treatment of demographic attributes [15]. More recent empirical work has investigated demographic and intersectional bias in resume screening using language-model retrieval [16]. A separate study specifically examined gender equity in resume-job matching [19]. These findings support a human-in-the-loop interpretation for educational career-support systems. Compared with these approaches, the present system is narrower in algorithmic ambition but broader in student-facing feedback. It does not claim to outperform specialized recommendation models or commercial ATS platforms. Instead, it combines a compatibility estimate with matched skills, missing/insufficiently represented skills, and recommendations. This makes the system useful for explaining what a student can improve before submitting an application.

Additional recent work broadens the context for career recommendation and AI-assisted resume support. AI-based career recommendation has been studied using occupational classification and sequence models [20], while zero-shot ESCO skill matching with large language models has been explored as an alternative to fully supervised extraction [21]. LLM-based resume completion has also been investigated as a way to improve downstream job recommendations [22]. Recent multimodal and semantic job-matching frameworks further indicate a trend toward combining heterogeneous candidate evidence with language-based matching [23]. Finally, practical end-to-end resume analysis systems have combined information extraction, semantic similarity, job aggregation, and career advice [24], [25]. These studies reinforce the need to distinguish a research prototype's functional scope from claims of general predictive superiority.

2.1 Research Gap

The literature contains strong solutions for individual components such as resume extraction, skill extraction, taxonomy alignment, recommendation, and job ranking. However, the reviewed approaches differ in their target users, datasets, objectives, and evaluation metrics. The research gap addressed here is therefore not the claim that no resume-matching system exists. Rather, the gap is the integration of job-specific compatibility estimation, explicit skill-gap interpretation, and actionable student-oriented recommendations in a lightweight web workflow. The current work also emphasizes transparent interpretation and human review instead of autonomous recruitment decisions.

3. Proposed Methodology

The proposed methodology uses two primary inputs: (i) a student's resume in PDF format and (ii) the job description of a target position. The job description is essential because suitability is role-dependent. A resume can be highly relevant to one position and less relevant to another because technical requirements, tools, responsibilities, education, and experience differ. The overall framework of the system is summarized in Figure 1, and Figure 2 shows the six sequential stages of the workflow: resume upload, text extraction, normalization of the resume and job description, AI analysis, structured JSON output, and display on the student dashboard.

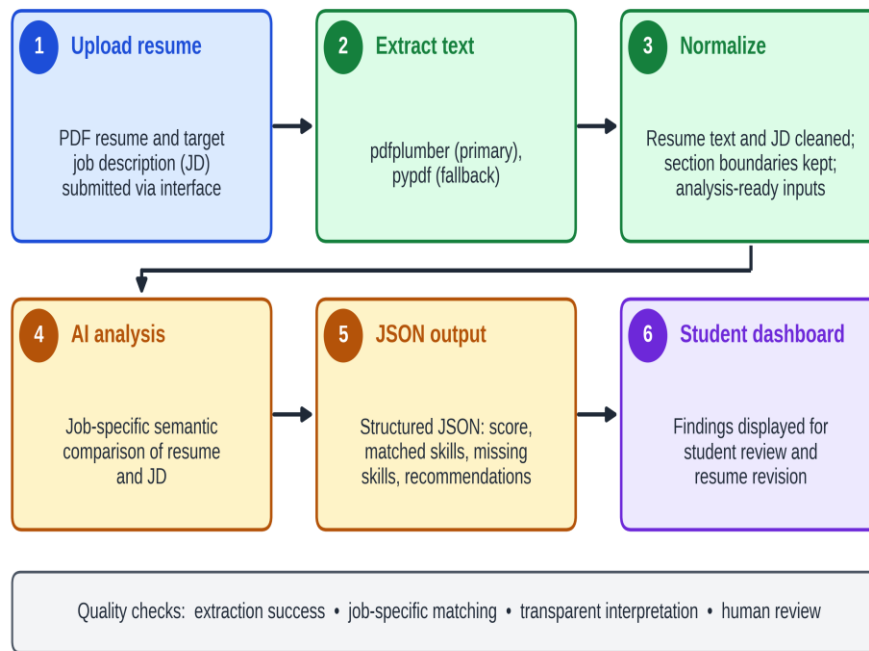


Fig. 2. Proposed methodology and workflow, showing the six sequential stages from resume upload to the student dashboard, with the quality checks applied throughout.

3.1 PDF Text Extraction and Normalization

The uploaded resume is processed using pdfplumber as the primary extraction library, with pypdf available as a fallback. The extracted text is normalized before analysis by removing unnecessary whitespace, preserving section boundaries where possible, and retaining the textual evidence required for skill and experience interpretation. This design follows the implementation described in the original submission [source implementation description]. Resume extraction remains a potential error source because multi-column layouts, icons, tables, images, and unusual formatting may affect the recovered text [9], [10].

Figure 2 illustrates the separation between document processing and AI analysis. This modular structure is important because extraction errors should be distinguishable from semantic matching errors during future evaluation.

3.2 Job-Specific Semantic Analysis

The normalized resume text and target job description are passed together to the AI analysis component. The analysis is job-specific: the same resume can receive different results when evaluated against different job descriptions. The model is instructed to return structured fields rather than unrestricted prose. The expected fields are compatibility score, matched skills, missing/insufficiently represented skills, and recommendations.

The analysis layer is intended to capture contextual relationships between requirements and evidence. For example, 'machine learning using Python and scikit-learn for classification' provides stronger contextual evidence for a machine-learning position than the isolated appearance of the word 'Python'. This principle is consistent with the broader literature on contextual skill extraction and semantic matching [7], [11], [12].

3.3 Revised Compatibility Score Structure

To address Reviewer 1's request for a clearer scoring mechanism, the revised manuscript formalizes the score as an interpretable composite. The score is represented as:

$$C = 0.50 S + 0.30 M + 0.20 E$$

where C is the compatibility score (0–100), S is required-skill coverage, M is semantic relevance between resume evidence and job requirements, and E is evidence strength from education, projects, internships, certifications, and experience. The weights emphasize explicit job-required skills while still allowing contextual evidence to contribute.

For skill coverage, S is calculated conceptually as the proportion of required skills sufficiently represented in the resume after normalization of equivalent terminology. Semantic relevance M captures contextual correspondence between the resume and job description, while evidence strength E reflects whether matched skills are supported by concrete resume evidence such as projects, responsibilities, certifications, or experience. These components are intended as an interpretable design specification for the revised methodology; the current implementation's sample scores remain implementation-level outputs and should not be interpreted as externally validated predictive probabilities.

This formulation also clarifies an important distinction: a 'missing skill' means that the requirement is not sufficiently evidenced in the supplied resume. It does not prove that the candidate does not possess the skill. This distinction is particularly important for students, whose practical skills may be acquired through coursework, self-learning, or projects and may be described using different terminology.

3.4 Skill Matching and Skill-Gap Identification

Matched skills are requirements from the job description that have corresponding evidence in the resume. Missing or insufficiently represented skills are requirements for which adequate resume evidence is not identified. The system should preferably normalize synonyms and related expressions before classification. Future versions can strengthen this stage through standardized taxonomies such as ESCO or O*NET, as demonstrated in recent research [4], [12].

The output is deliberately framed as a resume-level diagnostic. If 'TensorFlow' is absent from the resume, the system should report that TensorFlow is not sufficiently represented rather than asserting that the student cannot use TensorFlow. This wording improves interpretability and reduces the risk of turning incomplete documentation into an unsupported statement about candidate ability.

3.5 Recommendation Generation

Recommendations are generated from the identified differences between the resume and job description. Recommendations can address three situations: an existing skill should be represented more clearly; a relevant project or experience should be described with stronger evidence; or the candidate may need additional learning when the skill is genuinely absent. This produces a progression from evaluation to explanation and action.

4. System Implementation

The resume-analysis module is implemented as part of an AI-Powered Smart Campus & Career Hub using Python and Streamlit. Streamlit provides the interactive interface, Python coordinates document processing and analysis, and SQLite is available for local data persistence in the broader application. External AI services identified in the original project documentation include Google Gemini API and OpenAI API.

The system architecture separates four logical layers: input/interface, document extraction, AI analysis, and result presentation. The AI layer returns structured JSON fields so that the user interface can display the compatibility score, matched skills, missing skills, and recommendations independently. This modular architecture allows future replacement or augmentation of the AI model without redesigning the user interface.

4.1 Implementation Workflow

Stage	Input	Processing	Output
1. Upload	PDF resume	File validation and loading	Resume document
2. Extract	Resume PDF	pdfplumber; pypdf fallback	Extracted text
3. Normalize	Resume text + job description	Cleaning and contextual preparation	Analysis-ready inputs
4. Analyze	Resume + job description	AI-based semantic comparison	Structured JSON
5. Interpret	Structured JSON	Score, skill-gap and recommendation organization	Student-facing findings

6. Review**Findings****Human/student
verification****Final action plan**

The workflow is intentionally human-in-the-loop. The system provides evidence-based assistance but does not make hiring decisions. This is consistent with the ethical concerns documented in recent research on AI-assisted recruitment [14]–[16].

5. Experimental Evaluation*5.1 Evaluation Scope*

The current evaluation is a functional implementation test rather than a large-scale statistical benchmark. Three technical resume/job cases reported in the original implementation were retained: Python Software Engineer, AI/ML Engineer, and Data Scientist. The purpose of this evaluation is to verify that job-specific inputs produce differentiated compatibility estimates. Because no sufficiently large human-labeled dataset was available in the submitted study, accuracy, precision, recall, F1, and ranking metrics are not claimed for the proposed system.

Sample target role	Compatibility score (%)
Python Software Engineer	78
AI/ML Engineer	64
Data Scientist	71
Mean	71.0
Range	64–78

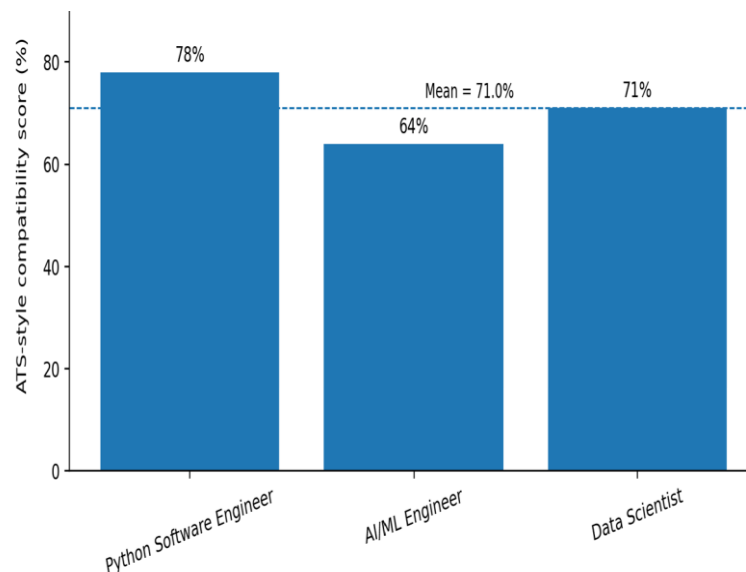


Fig. 3. Reported implementation-level sample compatibility scores. The dashed line indicates the arithmetic mean of the three sample scores.

As shown in Figure 3, the three cases produce different scores. The arithmetic mean is 71.0%, and the observed range is 14 percentage points. These differences are consistent with the intended job-specific behavior of the system: a single resume is not assigned a fixed universal score independent of the target position. However, the three cases are too small to support statistical generalization.

5.2 Comparative Analysis with Existing Approaches

Reviewer 2 requested a comprehensive comparison and graphical analysis. Table 4 compares representative recent approaches according to their primary function, matching strategy, reported evaluation evidence, and student-facing feedback. The reported metrics come from the cited studies and are not directly comparable because the datasets, tasks, metrics, and evaluation protocols differ.

Approach	Primary focus	Core technique	Reported evaluation evidence	Student-facing skill-gap/recommendation output
Gnehm et al. [7]	Skill extraction	Transformer representations + ESCO	MAP = 0.969 at skill-class level in reported setting	No
Huang et al. [5]	Resume recommendation	Attention-based deep neural model	F1@6, F1@15, NDCG@6, NDCG@15 improvements reported	No
Kavas et al. [4]	Multilingual skill matching	ESCO + knowledge graph + embeddings	Improved matching quality over state of the art	Limited
Alonso et al. [12]	Resume-job matching + skills	Transformers + O*NET semantic similarity	Outperformed baselines in reported scenarios	Yes
Raghavendra & Sheelavathy [25]	End-to-end resume analysis	NER + keyword filtering + semantic similarity	Information-extraction accuracy = 91.2%; processing 1–3 s/resume	Yes
Proposed system	Student-oriented resume analysis	PDF extraction + AI semantic comparison + structured feedback	3 implementation cases: 78%, 64%, 71%; no validated accuracy claim	Yes

The comparison indicates that the proposed system's distinction is primarily functional integration rather than a claim of superior predictive performance. Several existing studies report stronger quantitative evaluations on dedicated datasets [4], [5], [7], [12]. The proposed system instead emphasizes a lightweight student workflow that combines compatibility estimation, explicit matched/missing skill lists, and recommendations.

Figure 4 complements Table 4 by showing, at a glance, which functional capabilities are supported by representative approaches. Each row is an approach: keyword/NLP-based resume screening [8], RINX-style information extraction [10], the attentive deep-learning recommender AIRANN [5], and O*NET-based transformer matching [12], followed by the proposed system. Each column is one of six capabilities: resume parsing, semantic/AI matching, skill extraction/matching, skill-gap feedback, recommendations, and student-facing explanation. A check mark means the cited system description explicitly reports the capability; a dash means it is not reported, which does not imply that it could not be added. As Figure 4 shows, all four existing approaches cover resume parsing and skill extraction or matching, and the keyword/NLP screening approach is the only one without semantic matching. Only the O*NET-based transformer approach also provides skill-gap feedback and recommendations, and none of the four existing approaches explicitly offers a student-facing explanation. The proposed system is the only approach in the comparison that covers all six capabilities. This reflects functional coverage only: it is not a performance score and does not imply higher accuracy than the cited methods, whose reported quantitative results are summarized in Table 4.

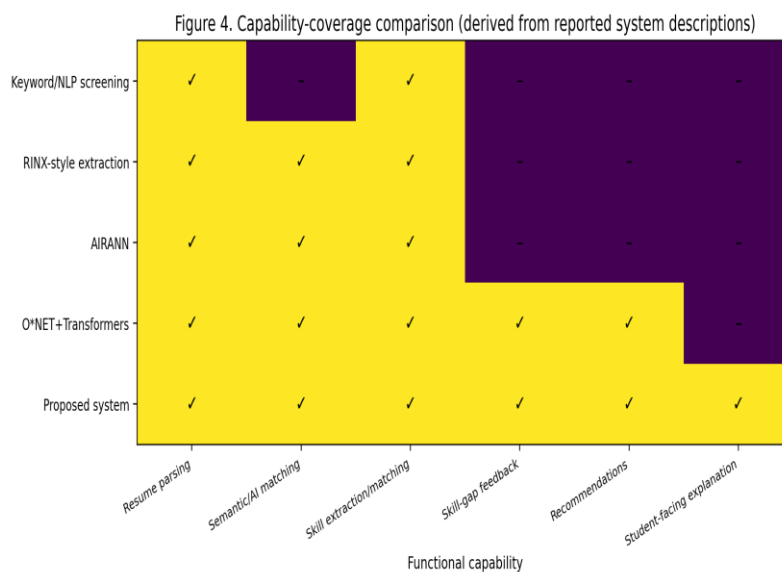


Fig. 4. Capability-coverage comparison derived from the functional descriptions of representative approaches. A check mark indicates that the cited approach explicitly supports the capability in its reported system description, and a dash indicates that it is not reported; this is not a performance score.

5.3 Discussion of Results

The reported scores of 78%, 64%, and 71% provide evidence that the implementation responds to the relationship between a resume and its selected target role. The lower AI/ML Engineer score, for example, should not be interpreted as evidence that an AI/ML candidate is less capable. It only indicates that the supplied resume provided less alignment evidence under the system's job-specific analysis for that case.

The main practical value of the system is therefore not the percentage alone. A score becomes actionable when accompanied by the matched skills, missing/insufficiently represented skills, and recommendations. This is consistent with the broader research direction toward skill extraction, taxonomy alignment, and semantic job matching [1], [4], [6], [12].

The current results also demonstrate why a larger benchmark is needed. A rigorous evaluation should include multiple resumes per role, multiple job descriptions per role, human-labeled relevance judgments, repeated runs where AI variability is possible, and baseline methods such as keyword overlap, TF-IDF/cosine similarity, and transformer embedding similarity. Evaluation should include precision, recall, F1 for skill identification and ranking metrics such as NDCG or Recall@K for job matching where appropriate.

6. Limitations

Dataset size: The present evaluation uses a small number of implementation-level cases and cannot establish population-level effectiveness.

Benchmark validation: Human-labeled resume-job relevance data and expert judgments were not available for the current study, so predictive accuracy metrics are not claimed.

PDF extraction: Complex layouts, columns, tables, images, icons, and scanned documents can reduce extraction quality.

AI variability: External AI services can produce different outputs depending on model version, prompt, context, and input quality.

Taxonomy coverage: The current implementation does not yet provide a complete standardized ESCO/O*NET skill ontology; future versions can use taxonomy alignment to improve consistency.

Fairness and governance: AI-assisted recruitment can reproduce or amplify biases in data and models [14]–[16], so the system should not be used as an autonomous hiring decision maker.

Score interpretation: The compatibility score is an internal decision-support estimate, not a commercial ATS score and not a probability of employment.

7. Conclusion

This revised paper presented an AI-based resume analysis and job-matching system designed to support engineering students during job preparation. The system processes a PDF resume and a target job description, extracts resume text, performs AI-based comparative analysis, and generates four structured outputs: an ATS-style compatibility estimate, matched skills, missing or insufficiently represented skills, and actionable recommendations. The revised methodology addresses the reviewers' request for greater scoring transparency by defining the compatibility estimate through required-skill coverage, semantic relevance, and evidence strength. The implementation-level evaluation retained the original sample results of 78%, 64%, and 71%, with a mean of 71.0%. These results demonstrate functional differentiation across job-specific cases but are explicitly not presented as accuracy or generalizable predictive performance. The literature comparison shows that recent research has achieved substantial progress in resume extraction, skill taxonomy alignment, semantic matching, and recommendation. The contribution of the proposed system is its integration of these functions into a lightweight, student-facing decision-support workflow. The system is intended to help students understand and improve their resumes rather than replace recruiters or make employment decisions.

8. Future Research

Develop a benchmark dataset containing engineering student resumes and job descriptions across multiple roles, with expert annotations for required skills, matched skills, skill gaps, and overall relevance. Evaluate skill extraction using precision, recall, and F1, and evaluate job matching using Recall@K, Precision@K, MRR, and NDCG where appropriate. Compare the proposed AI approach against keyword overlap, TF-IDF/cosine similarity, transformer embeddings, and taxonomy-based matching under the same dataset and evaluation protocol. Integrate ESCO and O*NET taxonomies to normalize synonyms, related skills, and hierarchical relationships. Recent work shows that taxonomy-aware matching can improve consistency across heterogeneous job language [4], [12]. Study representation gaps separately from actual skill gaps by asking users to confirm whether a detected missing skill is absent or simply not stated in the resume. Conduct fairness audits using controlled resume pairs and report performance and disparity measures across relevant demographic attributes, following the concerns raised in recent AI recruitment research [15], [16], [19]. Investigate explanation quality through human evaluation, including whether students understand why a score was produced and whether recommendations are actionable. Extend the system to role-specific resume versions, interview-question generation, project recommendations, and course recommendations while retaining human oversight. Evaluate robustness across resume formats, languages, job domains, and AI model versions to determine whether the system maintains stable behavior under realistic variation.

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