

AI-Powered Recruitment and Interview Platform: An Intelligent System for Resume Analysis, Candidate Screening, and Interview Preparation

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Abstract - Manual resume screening remains the default approach in recruitment pipelines but it does not hold up well against the volume of applications generated by modern job portals and it is susceptible to inconsistency and bias. The AI-based tools that have emerged to address this problem tend to handle one stage of the pipeline at a time. Resume parsing, keyword matching or a fixed bank of interview questions. With little integration across resume analysis, semantic candidate-job matching and interview preparation. This paper reviews work in Natural Language Processing (NLP) transformer-based semantic matching and Large Language Model (LLM)-based recruitment and interview systems and on that basis proposes a conceptual AI-Powered Recruitment and Interview Platform that brings together resume parsing, candidate-job matching, explainable screening and resume-aware interview preparation with personalized feedback in one framework. Fairness, privacy, explainability and human oversight are treated as core requirements of the design than features added afterward. The framework has not been implemented or experimentally validated; it is offered as an architecture, built from the surveyed literature intended to guide future work on fair and effective AI-assisted recruitment systems.

Keywords - Artificial Intelligence, Resume Analysis, Candidate Screening, Natural Language Processing, Semantic Matching, Large Language Models, Interview Preparation, Recruitment Automation Explainable AI.

I. INTRODUCTION

In organizations recruitment still starts with someone manually reading through resumes to judge candidates skills, education and experience against a jobs requirements [1] [3]. A single posting on a job portal or a corporate careers page can draw hundreds or thousands of applications and recruiters are usually expected to narrow this down to a shortlist within a tight timeframe. That pressure makes manual screening inconsistent prone to reviewer fatigue and hard to audit after the fact. Which is part of why recruitment automation has attracted research interest [2] [4].

Artificial Intelligence has found its way into every stage of this pipeline. NLP and Named Entity Recognition (NER) pipelines now convert resume text into structured candidate profiles [4]–[7] and candidate-job matching has moved on from simple keyword overlap to transformer-based semantic embeddings. BERT and Sentence-BERT among them. That capture contextual meaning instead of just counting shared terms [8]–[10]. Recently Large Language Models (LLMs) have added the ability to generate natural-language explanations for match scores produce resume-aware interview questions and give personalized feedback on candidate responses [11]–[13].

So resume analysis, candidate screening and interview preparation have largely developed as separate research threads and separate commercial products. A job seeker might use one tool to get a resume past an Applicant Tracking System, another to check job fit and a third unrelated tool to practice for interviews. Because these pieces don't talk to each other interview preparation ends up disconnected from the gaps a matching system identifies and recruiters are left without a single transparent account of why a candidate was ranked or recommended [11]–[13].

This paper surveys these research threads. Proposes a conceptual integrated platform that ties resume analysis, semantic matching, explainable screening and personalized interview preparation into a single framework treating fairness, privacy and human oversight as design requirements from the outset rather than as afterthoughts [14]–[17]. The rest of the paper is organized as follows. Section II reviews the literature. Sections III and IV set out the problem statement and research gap. Section V presents the proposed conceptual methodology and Section VI describes the system architecture. Sections VII–X cover expected outcomes, advantages, limitations and future scope and Section XI concludes the paper.

II. LITERATURE SURVEY

A. Resume Parsing and Information Extraction

The earliest automated screening systems relied on keyword and rule-based filtering [1] [3]. These sped up processing to fully manual review but they could not recognize skills that were semantically equivalent yet phrased differently. Alamelu et al. [3]. Harsha et al. [5] Use NLP pipelines to extract resume fields and cut down on review effort and Ali et al. [4] Combine NLP with machine-learning classifiers for resume categorization. Bhatia et al. [8] Build an end-to-end resume-parsing system on BERT that markedly improves candidate-attribute identification compared with rule-based extraction while Sajid et al. [6] Present a parsing framework aimed specifically at the variation found in resumes submitted to e-recruitment platforms.

B. Semantic and Transformer-Based Matching

A second strand of work matches resumes to job descriptions using learned representations instead of lexical overlap. Lavi et al. [9] Build on the Transformer architecture [19] to introduce conSultantBERT a tuned Siamese Sentence-BERT model adapted for job-seeker matching and show that domain-specific contrastive fine-tuning outperforms generic embeddings by a wide margin. Reimers and Gurevych [10] propose Sentence-BERT itself using triplet network structures to derive sentence embeddings that can be compared efficiently via cosine similarity. A technique that now sits underneath most modern semantic recruitment-matching systems. Bian et al. [18] Take an angle framing resume-job matching as a sparse interaction-learning problem and proposing a multi-view co-teaching neural network to work around the scarcity of reliable hiring-outcome labels.

C. LLM-Based Recruitment and Interview Systems

General-purpose LLMs such as GPT-4 [20] have brought capabilities to recruitment. Natural-language explanations of match scores on-the-fly interview-question generation and automated feedback among them [11]–[13]. Joko et al. [11] Describe an interview bot that combines NLP and machine learning to run structured interviews and Guo et al. [12] Survey LLM-based multi-agent frameworks that offer a basis for simulating interviewer-candidate dialogue. Across the systems reviewed here though question generation is typically treated as a standalone module disconnected from resume-job matching results, which limits how well practice questions reflect a candidates role-specific skill gaps.

D. Fairness, Bias and Explainability

Bertrand and Mullainathan [21] offer some of the most cited field-experiment evidence of discrimination in human-mediated hiring callbacks and their results still serve as a baseline against which algorithmic systems get compared. More recent work has turned that lens on LLMs: An et al. [14] Find racial and gender disparities in LLM-generated hiring recommendations and Wang et al. [15] Introduce JobFair, a benchmark for measuring gender-based hiring bias across LLMs. Raghavan et al. [16] Review commercial hiring. Find that vendors fairness claims are frequently unsubstantiated, largely because of limited transparency and Mehrabi et al. [17] Lay out a taxonomy of bias and fairness

definitions that applies to machine-learning systems in general. Kline et al. [22] Use a large-scale correspondence-audit methodology to quantify discrimination among major employers and Geyik et al. [23] Describe a fairness-aware ranking framework deployed in a large-scale professional talent-search system. Taken together this body of work recommends explainability and human oversight enough but rarely builds them into applied resume-screening or interview-preparation systems as actual architectural components.

Table I. Comparative Analysis of Existing AI-Based Recruitment Systems

Ref.	Method	Sem. Match	Interview Prep.	Explainable	Limitation
[1]	Keyword filtering	✗	✗	✗	No understanding
[4]	NLP + ML classifier	✓	✗	✗	Domain-specific training needed
[6]	Rule-based parser	✗	✗	✗	Struggles with layout variance
[8]	BERT parsing	✓	✗	✗	High compute cost
[9]	conSultantBERT	✓	✗	✗	Needs labelled domain data
[10]	Sentence-BERT	✓	✗	✗	Fine-tuning dependent
[11]	LLM mock interview	✗	✓	✗	No resume-match linkage
[12]	Multi- LLM	✗	✓	✗	Conceptual, generic domain
[14]	LLM bias audit	✗	✗	✓	Audit only, no system
[16]	Fairness policy review	✗	✗	✓	No implementation proposed
[18]	Co-teaching network	✓	✗	✗	Requires interaction logs
Proposed	Hybrid semantic + LLM	✓	✓	✓	Conceptual, not yet implemented

Table I lays out a clear progression from lexical to semantic to generative techniques but it also shows that none of the reviewed systems combine semantic matching, resume-aware interview preparation and explainability in a single pipeline. Fairness and bias auditing has been studied extensively at the evaluation level [14]–[17]. It is rarely built in as a design constraint within the applied matching and interview systems covered in Sections II-A through II-C. That gap between audit-level findings and applied-system design is what motivates the integrated architecture proposed in Section V.

III. PROBLEM STATEMENT

The literature reviewed above points to a recurring set of problems, in existing recruitment systems:

- Manual resume screening does not scale to applicant volumes and produces inconsistent evaluations [1] [3].
- Keyword-based matching fails to recognize equivalent or transferable skills [1] [8]–[10].
- Candidate-job matching outputs are often unclear giving little indication of why a candidate was ranked or rejected.
- Resume screening and interview preparation are fragmented across disconnected tools so interview practice is not informed by identified skill gaps [11]–[13].
- Algorithmic bias documented in LLM-based hiring studies [14]–[16] is rarely mitigated as a design constraint in deployed screening or interview tools.
- Sensitive candidate data is processed with attention to privacy and security safeguards.

Together these problems point to the need for an integrated fairness-aware platform that connects semantic candidate-job matching to personalized, resume-aware interview preparation with a human retained in the loop.

IV. RESEARCH GAP

What emerges from the literature is progress that's mature in each individual area but siloed across areas. Semantic matching research [8]–[10] [18] rarely connects to interview-preparation research [11]–[13]. Fairness and bias

findings [14]–[17] are seldom built into applied screening or interview tools as design constraints and standardized datasets and LLM-specific evaluation frameworks for recruitment are still immature. Human-in-the-loop mechanisms show up often as a recommendation. Rarely as an actual architectural component and multilingual or adaptive interview systems remain comparatively underexplored next to static English-centric question banks. These gaps, taken together motivate the integrated system proposed in Section V.

V. PROPOSED METHODOLOGY

The proposed system is a conceptual framework rather than an implemented or experimentally validated one. It is organized into the following stages.

A. Resume and Job-Description Ingestion

Candidates and recruiters can upload resumes and job descriptions as PDF or DOCX files, which are then normalized before next steps process.

B. Information Extraction

An NLP/NER extraction module identifies skills, education, experience, certifications and projects from resumes [4]–[7]. A parallel module does the same for job descriptions pulling out required and preferred qualifications so that both sides end up as structured profiles.

C. Semantic Matching and Ranking

A semantic matching engine combines TF-IDF, transformer embeddings such as Sentence-BERT [10] and cosine similarity to produce decomposed match scores. Skill, experience and education. Along with an explanation that lists missing skills and strengths. These outputs are intended as decision support final authority over shortlisting and hiring decisions stays with a human recruiter [8] [9].

D. Resume-Aware Interview Preparation

If a candidate moves on to interview preparation, an LLM-based module generates HR and behavioral questions that are aware of both the resume and the role calibrated to the candidates assessed experience level. These questions are drawn directly from the gaps identified during matching than pulled from a generic static bank.

E. Answer Evaluation and Feedback

Candidate responses are evaluated on relevance, technical correctness, completeness and clarity and the resulting feedback report highlights strengths, weaknesses and topics worth practicing. In line with the cautions raised in Sections II-C and II-D the framework makes no claim to infer personality, honesty or mental state from candidate responses.

VI. SYSTEM ARCHITECTURE

Fig. 1 Summarizes the end-to-end conceptual data flow. Candidates and recruiters both interact through a shared Web/Mobile Interface and Authentication/API layer. Uploaded resumes and job descriptions go through NLP-based information extraction before reaching the Semantic Matching Engine, whose output. Candidate Screening & Ranking. Feeds the Recruiter Dashboard. When interview preparation is invoked the LLM-Based Interview Preparation module works from the structured candidate profile and candidate responses then flow through Answer Evaluation into Personalized Feedback. Extracted profiles, match results and evaluation records are stored in a database, backed by a vector database for efficient similarity search over dense embeddings. Than sitting as one more stage in the pipeline, Security, Privacy, Fairness, Explainability and Human-in-the-Loop review form a layer that cuts across every module since these concerns need to be addressed at each processing step not only checked at the output.

Fig. 1. Conceptual architecture of the proposed platform.

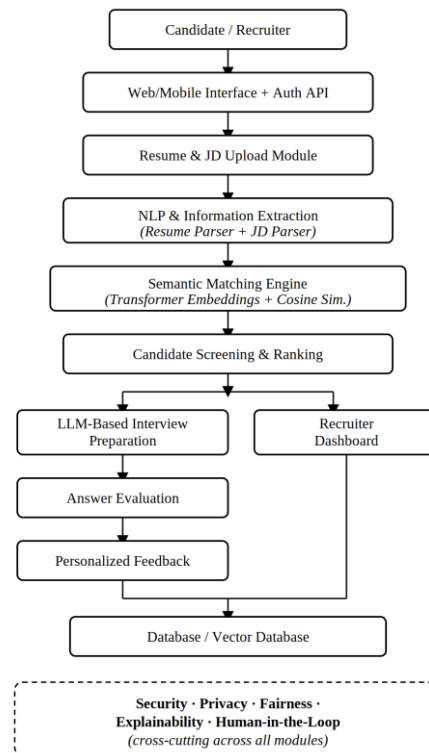


Fig. 1. Conceptual architecture of the proposed platform.

VII. EXPECTED OUTCOMES

The system is expected to bring the following benefits, which are anticipated than experimentally demonstrated:

- Faster more consistent resume analysis compared with fully manual review.
- Improved semantic job-resume matching over keyword- baselines.
- Explainable decomposed candidate-ranking factors that support recruiter trust.
- resume-aware interview questions and structured feedback.
- Earlier identification of candidate skill gaps relevant to a target role.
- Reduced repetitive manual workload for recruiters handling applicant pools.

VIII. ADVANTAGES

- Automates repetitive resume screening while retaining human decision authority.
- Improves job-resume matching through transformer-based understanding.
- Connects interview preparation directly to identified skill gaps.
- Provides decomposed match scores rather than opaque rankings.
- Embeds fairness, privacy and human-in-the-loop review as core design elements.
- Offers a coherent candidate journey from screening through interview practice.
- Scales to applicant volumes through a modular API-driven architecture.

IX. LIMITATIONS

- Matching and ranking quality depend on resume completeness and training-data quality.
- LLM components may. Vary in behavior across model versions [14]–[16].

- Fairness risks documented in audit literature require monitoring, not one-time mitigation.
- Evaluating soft skills and multilingual resumes remains difficult.
- Third-party LLM API dependency introduces cost, availability and version-drift risks.
- Requires continued supervision before any deployment in real hiring decisions.

X. FUTURE SCOPE

directions could extend this work: retrieval-augmented generation to ground LLM outputs and cut down on hallucination; fairness-aware ranking constraints built directly into the matching objective extending industrial approaches such as [23]; multilingual and multimodal resume understanding; adaptive real-time interview simulation that adjusts question difficulty to how the candidate is performing; and privacy-preserving training methods such as federated learning and differential privacy to protect sensitive candidate data across organizations. Further out, bias auditing and formal human-AI collaborative review workflows. Informed by correspondence-audit methodologies such as [22]. Would help keep the platform fair and trustworthy as it scales to new industries and regions.

XI. CONCLUSION

This paper has traced AI-powered recruitment technology from keyword-based screening through transformer- and LLM-based semantic matching and interview preparation. Pointed to a persistent gap. Between resume-screening and interview-preparation research and between bias/fairness findings and applied system design. Building on that gap it proposed a integrated AI-powered recruitment and interview platform that unifies resume analysis, semantic matching, explainable screening and personalized interview preparation under a human-in-the-loop fairness-aware framework. The framework remains conceptual; what comes next is. Empirically validating this design while working through the bias, privacy and reliability limitations discussed above.

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