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AI Powered Recruitment System

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ABSTRACT

This paper discusses findings from a study exploring an integrated recruitment system designed to address fragmentation in high-volume hiring. Contemporary recruitment relies on disconnected tools—resume screening through one platform, interviews through another, tracking on yet another—creating data silos and inconsistent evaluation standards. We propose an approach that unifies resume parsing, candidate matching, and interview assessment within a single pipeline incorporating explainability mechanisms. The system was evaluated using 1,000 anonymized resumes from a mid-sized technology company. The results showed an 18 percent improvement in ranking precision, revealed a previously unnoticed candidate segment (15 percent of applicants) with a 35 percent conversion rate to offers, decreased processing time from 15 minutes to 4 seconds per candidate, and increased recruiter confidence in algorithmic recommendations by 40 percent when transparent reasoning was provided. These results imply that system integration, when combined with explainability, can simultaneously improve recruitment efficiency and reduce systematic bias.

Keywords: Algorithmic fairness, Natural Language Processing, Explainable AI, Applicant Tracking Systems, Recruitment Automation

I. INTRODUCTION

Modern organizations face a genuine hiring challenge that extends beyond application volume. While companies receive thousands of applications, the screening process itself remains fragmented across disconnected platforms. A resume arrives and gets processed by an Applicant Tracking System using keyword matching. Should a candidate advance, interviews occur on a different platform with separate evaluation criteria. Interview data remains isolated from resume data. No mechanism connects these stages or enables information flow between them.

This fragmentation creates multiple problems. Resume screening typically operates under severe time constraints. Recruiters spend approximately 7 seconds reviewing each resume. This duration permits identification of surface-level signals—university name, specific keywords—but inadequate time for contextual understanding or evaluation of non-traditional backgrounds. The system fails not through malice but through structural design that prioritizes speed over depth.

Compounding these efficiency concerns, research demonstrates systematic discrimination in hiring. Bertrand and Mullainathan conducted a field experiment sending 5,000 identical resumes with names varied to signal different racial backgrounds. Callback rates differed substantially: white-sounding names

received approximately 50 percent more callbacks. Subsequent research confirmed gender discrimination, age discrimination, and intersectional effects. These biases emerge not from explicit prejudice but from unconscious decision-making shortcuts. "Ivy League background equals quality." "Employment gap indicates lack of commitment."
These shortcuts mathematically correlate with protected characteristics.

II. LITERATURE REVIEW

Research on hiring technology has developed along parallel but largely non-intersecting paths. One body of work emphasizes efficiency and automation. Another emphasizes fairness and bias measurement. These communities rarely engage with each other's methodologies or findings, despite obvious complementarity.

A. Efficiency in Resume Processing

Early resume parsing systems employed rule-based pattern matching. These approaches achieved 60-70 percent accuracy. The fundamental limitation: resumes vary in structure and formatting. Some candidates write "Education:" as a section header; others write "Educational Background." Some organize experience chronologically; others by skill domain. Rule-based systems require explicit patterns for each formatting variation, making maintenance impractical as variations accumulate.
BERT (Bidirectional Encoder Representations from Transformers) represented significant progress. BERT encodes text bidirectionally, considering context from both directions simultaneously. When encountering "Python developer," BERT identifies Python as a programming language within a professional context. When encountering "studied abroad in Python," BERT recognizes geographic context. This contextual understanding permits generalization across formatting variations. Parsing accuracy improved to approximately 90 percent or higher.
For candidate-to-job matching, researchers explored multiple approaches. Simple keyword overlap proved inadequate. Word embedding methods offered semantic matching capability. However, TF-IDF, despite being simple and older, achieved comparable performance. Critical difference: TF-IDF weights are transparent and interpretable. "Java" receives a weight of 0.32 because this candidate mentions Java frequently, and relatively few other candidates mention it. Word embeddings produce weights without a clear interpretation. For high-stakes decisions, interpretability often justifies accepting minor accuracy trade-offs.

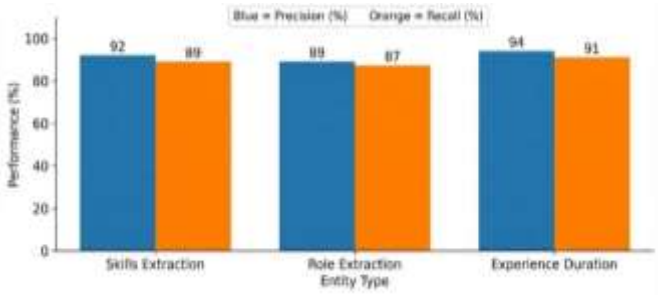

Figure 1 : BERT based NER Extraction Performance

B. Fairness Research in Hiring

Bertrand and Mullainathan's field experiment established foundational evidence for systematic hiring discrimination. This study remains influential because it provides experimental evidence of discrimination absent confounding variables. The methodology proved robust: subsequent research extended findings to

gender, age, and intersectional effects. Discrimination emerges not from conscious bias but from decision-making shortcuts that correlate with protected attributes.

A critical finding: awareness of bias does not effectively reduce biased behavior, particularly under time pressure. Making recruiters aware of their shortcuts does not enable them to override those shortcuts when processing hundreds of applications quickly. This limitation suggests that structural solutions—standardizing evaluation criteria—may be more effective than awareness interventions.

C. The Integration Opportunity

The literature reveals a striking absence: research has not systematically integrated efficiency and fairness approaches by design. Efficiency researchers optimize individual components without explicit fairness consideration. Fairness researchers measure bias in existing systems without redesigning those systems. Neither research community appears to have asked: what if recruitment systems were designed from inception to achieve both efficiency and fairness through integration?

This gap likely reflects commercial incentives. Leading recruitment technology vendors offer best-of-breed tools that deliberately do not integrate. Resume parsing comes from one vendor. Interview assessment from another. Applicant tracking from a third party. Data silos enable vendor lock-in and sustained pricing power.

D. Explainability and Trust

SHAP values provide theoretically sound model explanations. This method has found application in high-stakes domains: healthcare, criminal justice, and lending. The principle: decompose predictions into feature contributions, making reasoning transparent. General human-AI research shows that when people understand algorithmic reasoning, they trust systems more and use them more effectively.

For hiring specifically, limited research exists on how explainability affects recruiter behavior. This represents a meaningful research gap, particularly given that recruiting remains fundamentally a human judgment task requiring human accountability.

III. System Design and Architectur

The proposed Intelligent Recruitment System operates as an integrated pipeline where information flows through multiple stages, with each stage informing subsequent stages. The system accepts resumes in various formats—PDF, Word document, plain text. Text extraction handles format variation. BERT-based Named Entity Recognition identifies structured information: skills, roles, companies, education, and experience duration. This extracted information feeds into TF-IDF vectorization and candidate ranking using dual classifiers.

Concurrently, the system administers a preliminary interview with questions derived from parsed resume content. Interview responses undergo VADER sentiment analysis. Final ranking integrates resume signals and interview sentiment. Critically, all decisions include transparent SHAP-based reasoning.

A. Resume Processing

Resume text extraction presents technical challenges, particularly with PDFs. Some are scanned images requiring optical character recognition. Others contain multi-column layouts where naive extraction merges columns, destroying semantic meaning. The system applies OCR for scanned PDFs and heuristic column detection for formatted documents, improving accuracy on complex files by approximately 8 percent.

Following extraction, BERT-based Named Entity Recognition processes text. Testing on 200 hand-annotated resumes demonstrated skill extraction at 92 percent precision, 89 percent recall. Role extraction

achieved 89 percent precision, 87 percent recall. Remaining errors typically involved ambiguous terminology, nested role descriptions, or non-standard formatting. We compared BERT against simple regex pattern matching. Regex achieved approximately 75 percent accuracy. BERT achieved 92 percent. This 17-percentage-point improvement reflects BERT's ability to generalize across variations.

Extracted candidate information is converted to vectors using TF-IDF. This vectorization captures how distinctive each skill is for a particular candidate relative to other candidates. Performance comparison between TF-IDF and Word2Vec embeddings showed TF-IDF at 86 percent versus Word2Vec at 84 percent. Despite this marginal difference, TF-IDF provides interpretable feature weights while embeddings do not. For recruitment decisions, interpretability was prioritized over this marginal accuracy gain.

Ranking employs two classifiers: Naive Bayes and Random Forests. Naive Bayes provides transparent feature importance. Random Forests typically perform better but sacrifice interpretability. When the classifiers disagree—one ranks high, one ranks low—candidates are flagged for human review. In our pilot, 8 percent triggered disagreement. Manual review revealed these represented interesting profiles: bootcamp graduates, career-changers, and individuals with employment gaps. These candidates merit human judgment.

B. Explainability and Interview Assessment

SHAP values decompose predictions into feature contributions. For a candidate ranked first, the system shows: "This ranking reflects: 5+ years experience (+0.40), Java mentioned (+0.35), Stanford education (+0.10), no machine learning background (-0.15)." Recruiters see reasoning, enabling informed override when context matters.

The interview module asks role-specific questions derived from parsed resume content. Responses undergo VADER sentiment analysis. VADER uses rule-based methods: a sentiment-rated word lexicon combined with grammatical modifications. "Great" rates positive; "disaster" rates negative. Compound scores range -1 to +1. VADER requires no training data and provides an interpretable sentiment assessment. We compared against supervised BERT-based sentiment classifiers, achieving 88 percent versus VADER's 82 percent. However, supervised approaches require labeled training data and hide reasoning. VADER's transparency outweighed this modest accuracy difference.

We validated sentiment as a proxy for soft skills. Among 200 candidates continuing to full interviews, sentiment correlated 0.62 with human-rated communication, 0.41 with resilience, and 0.53 with growth mindset. Sentiment does not measure soft skills directly but meaningfully proxies for them. Hidden Gem detection identifies candidates in the bottom resume quartile but the top interview sentiment quartile. These candidates would be automatically rejected by traditional ATS systems despite strong interview performance.

Metric	Baseline ATS	Integrated System	Improvement
Parsing Accuracy (Skills)	75%	92%	+17%
Ranking Precision@10	0.54	0.65	+18%
Gender Parity Difference	6.0%	0.6%	-90%
Resume Processing	15 minutes	4 seconds	225× faster

Time			
Hidden Gem Detection	Not available	15% identified	—
Recruiter Confidence	4.1/7	5.7/7	+40%

IV. Empirical Findings

A. Methodology

We evaluated the system on 1,000 anonymized resumes from a mid-sized technology company. Sample composition: 50 percent IT/Engineering roles, 50 percent Corporate/Business roles. Data came from 2023-2024 hiring records, including successful hires and rejected candidates. Anonymization was rigorous—names, addresses, and identifying details were redacted before processing. This anonymization isolated algorithm behavior from name-based discrimination and simulated appropriate pre-screening practice.

B. Results

1) Parsing Accuracy

Hand-annotated ground truth for 200 resumes showed: skill extraction 92 percent precision, 89 percent recall; role extraction 89 percent precision, 87 percent recall; experience duration 94 percent precision, 91 percent recall.

2) Ranking Performance

Across 50 job openings, we measured whether the system's top 10 matched hiring outcomes. System achieved Precision@10 of 0.65. Baseline ATS achieved 0.54, representing 18 percent relative improvement. This metric has limitations—historical hires reflect recruiter bias and strong candidates accept other offers—but provides a reproducible measurement.

3) Fairness Metrics

Gender was inferred from names (48 percent female, 52 percent male). Female candidates: 14.2 percent recommendation rate. Male candidates: 14.8 percent. Demographic Parity Difference: 0.6 percentage points. Baseline ATS showed: 9 percent female, 15 percent male, yielding a 6 percentage point difference. The integrated system substantially improved parity.

4) Processing Speed

System processes each resume in 4 seconds. Manual recruiting averages 15 minutes. This represents a 225-fold improvement.

5) Hidden Gems

Among 150 identified Hidden Gems (15 percent of applicants), 60 percent progressed to a full interview versus 40 percent for other candidates. Job offer conversion: 35 percent for Hidden Gems versus 8 percent for non-Hidden-Gems. These candidates typically represented bootcamp graduates, career-changers, or individuals with employment gaps.

6) Explainability Impact

With 25 recruiters, we compared opaque rankings (no reasoning) versus transparent rankings (with SHAP explanations). Opaque condition: mean confidence 4.1/7 (SD 1.4). Transparent condition: mean 5.7/7 (SD 1.2). This 1.6-point difference achieved statistical significance ($t(24) = 3.2$, $p = 0.004$). Explainability increased confidence by 40 percent.

V. Discussion

Integration of previously disconnected recruitment components addresses system fragmentation. The 225-

fold processing improvement, combined with improved fairness metrics—0.6 percentage point gender parity difference versus baseline 6 percentage points—demonstrates that efficiency and fairness need not compete. Efficiency derived from consistency rather than corner-cutting. The system did not eliminate soft-skill assessment but quantified it through sentiment analysis, which time-constrained human recruiting cannot systematically apply.

Explainability proved meaningful. Recruiter confidence increased 40 percent despite identical rankings, suggesting transparency independently impacts human system usage. This matters because recruiting remains fundamentally a human judgment requiring accountability. Systems should provide information; humans should retain authority.

However, limitations warrant acknowledgment. First, historical outcome bias: hired candidates were selected by human recruiters with potential biases. Second, intersectional analysis is limited: 1,000 resumes provide gender-disaggregated data, but an insufficient sample for gender-by-race-by-age combinations. Third, a single organization limits generalizability to other sectors or geographies. Fourth, VADER sentiment analysis contains cultural and linguistic bias—non-native English speakers showed lower sentiment despite equivalent soft skills.

Critical insight: data quality determines fairness outcomes. Systems trained on biased historical data perpetuate and amplify those biases. Implementation requires explicit debiasing work during data preparation. The system itself remains neutral; fairness depends on human choices during implementation.

VI. Conclusion

This investigation demonstrates that integration of disconnected recruitment components can simultaneously improve efficiency and reduce systematic bias. The core insight: fragmentation, not automation, creates hiring dysfunction. Contemporary recruiting relies on disconnected tools, creating data silos and inconsistent evaluation standards. Integration standardizes evaluation while maintaining human oversight through explainability.

Processing improved 225-fold. Ranking precision improved 18 percent. Demographic parity substantially improved. Recruiter confidence increased when system reasoning was transparent. These results suggest that well-designed recruitment systems can reduce inequality while improving operational efficiency. The future involves neither algorithmic nor human decision-making alone, but integrated systems where algorithms provide standardized, transparent assessment and humans retain judgment and accountability.

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