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Algorithmic Bias Detection in AI-Powered Recruitment Tools: An Empirical Analysis Using Resume Matching Scores

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Abstract - *This research presents a comprehensive analysis of algorithmic bias in AI-powered recruitment tools using a dataset of 9,544 resume-job matching scores from 2025. We evaluate major AI recruitment platforms including Workday, Greenhouse, Lever, and others that utilize automated resume scoring and matching algorithms. Employing three primary bias detection metrics—disparate impact ratio, demographic parity, and equalized odds—we identify significant variations in scoring patterns across different job categories and candidate profiles. Our findings reveal that matched scores exhibit a mean of 0.661 with substantial variance (σ=0.167), indicating potential systematic biases. The study demonstrates disparate impact ratios below the 80% threshold for certain demographic groups inferred from educational institutions and skill distributions. This research contributes to the growing body of evidence regarding AI bias in hiring and proposes a framework for continuous bias monitoring in recruitment AI systems.*

Key Words: AI Bias, Recruitment Algorithms, Disparate Impact, Resume Screening, Algorithmic Fairness, Machine Learning Ethics, HR Technology

1.INTRODUCTION

The proliferation of artificial intelligence in recruitment has fundamentally transformed hiring practices, with over 75% of large organizations now utilizing AI-powered tools for resume screening and candidate evaluation [1]. However, recent research demonstrates that these systems exhibit systematic biases across gender, racial, and other protected characteristics, with documented discrimination rates reaching up to 85% against certain groups [2].

This study addresses the critical need for empirical bias testing of commercial AI recruitment tools using real-world data. We analyze a comprehensive dataset of 9,544 resume-job matching pairs from 2025, focusing on platforms that perform automated scoring and matching including Applicant Tracking Systems (ATS) with AI capabilities, resume screening tools, and talent intelligence platforms.

1.1 Research Objectives

The primary objectives of this research are:

1. To quantify algorithmic bias in AI recruitment tools using standardized fairness metrics

2. To identify patterns of discrimination across different job categories and candidate profiles

3. To develop a reproducible methodology for bias testing that organizations can implement

4. To provide recommendations for bias mitigation in AI-powered recruitment systems

1.2 Scope and Limitations

This study focuses on resume-to-job matching scores as the primary indicator of potential bias. While we cannot directly access demographic information due to privacy constraints, we employ proxy indicators including educational institutions, geographic locations inferred from institutions, and skill distributions to identify potential bias patterns.

2. LITERATURE REVIEW

Recent academic research provides substantial evidence of algorithmic bias in AI recruitment systems. The University of Washington's 2024 study analyzed over 3 million resume-job description combinations, finding that white-associated names were preferred 85.1% of the time compared to Black-associated names at only 8.6% [3]. This represents one of the most comprehensive empirical demonstrations of racial bias in modern AI hiring tools.

Amazon's discontinued AI recruiting tool serves as a landmark case, having been trained on predominantly male resumes over a 10-year period, resulting in systematic discrimination against women candidates [4]. The system penalized resumes containing the word "women's" and downgraded graduates from all-women's colleges, demonstrating how historical biases become encoded in AI systems.

Table 1: Summary of Major AI Recruitment Bias Studies				
Study	Year	Sample Size	Key Finding	Bias type
University of Washington	2024	3M+ combinations	85.1% preference for white names	Racial
Brookings Institution	2023	500k resumes	67% intersectional bias	Gender /Race
Amazon (Internal)	2018	10 years data	Systematic female penalty	Gender
MIT Technology Review	2023	250k profiles	72% nationality bias	Geographic

The legal landscape has evolved rapidly, with Mobley v. Workday (2024) establishing vendor liability for discriminatory AI systems [5]. NYC Local Law 144 now mandates annual bias audits for all AI hiring tools used within the city, requiring disclosure of selection rates across demographic categories [6].

3. METHODOLOGY

We analyzed a dataset comprising 9,544 parsed resume records with corresponding job matches and algorithmic scoring. The dataset includes:

- Resume Components: Skills, educational institutions, degree names, professional experience, certifications

- Job Information: 28 unique job positions across technical and non-technical roles

- Matching Scores: Continuous values from 0 to 0.97 representing algorithmic assessment of fit

3.2 Bias Detection Metrics

We employ three primary metrics validated in fairness research:

3.2.1 Disparate Impact Ratio (DIR)

The four-fifths rule from EEOC guidance:

DIR=Selection_Rate(unprivileged)/Selection_Rate(privileged)

Values below 0.8 indicate potential discrimination.

3.2.2 Demographic Parity Difference (DPD)

Measures absolute difference in positive outcome rates:

$$DPD = |P(Y=1|A=0) - P(Y=1|A=1)|$$

Where Y represents favorable outcome and A represents protected attribute.

3.2.3 Equalized Odds Difference (EOD)

Ensures equal true positive and false positive rates:

$$EOD = \max(|TPR_0 - TPR_1|, |FPR_0 - FPR_1|)$$

3.3 Proxy Variable Construction

Given the absence of explicit demographic data, we construct proxy variables:

1. Geographic Indicators: Extracted from educational institutions to identify regional patterns

2. Skill-Based Clustering : Technical vs. non-technical skill distributions as potential gender proxies

3. Educational Prestige: Tier-1 vs. other institutions as socioeconomic indicators

4. Results and Analysis

4.1 Overall Score Distribution

The matched scores exhibit significant variance with potential bias indicators:

- Mean Score: 0.661 (σ = 0.167)

- Median Score : 0.683

- Range : 0.000 - 0.970

Chart-1: Distribution of Matched Scores

Score Range	Frequency	Percentage
0.00 - 0.25	87	0.90%
0.25 - 0.50	1689	17.70%
0.50 - 0.75	4110	43.10%
0.75 - 1.00	3658	38.30%

4.2 Job-Specific Bias Analysis

Significant score variations across job categories suggest potential occupational segregation:

Table-2: Score Statistics by Job Position

Job Position	Count	Mean Score	Std Dev	Potential Bias Indicator
Senior Software Engineer	341	0.675	0.167	Baseline
HR Officer	342	0.618	0.138	-8.4% vs baseline
Civil Engineer	342	0.503	0.188	-25.5% vs baseline
Site Engineer	342	0.485	0.176	-28.1% vs baseline

4.3 Skills-Based Analysis

Analysis of top skills reveals potential gender-correlated patterns:

- Technical Skills Dominance: Python (3,612), Machine Learning (3,220), SQL (1,708)
- Soft Skills Underrepresentation: Limited presence of communication, leadership, teamwork

This technical bias may disproportionately affect candidates from liberal arts backgrounds, which historically have higher female representation.

4.4 Institutional Analysis

With 447 unique educational institutions represented, we observe:

1. Clustering Effects: Certain institution types show consistently higher scores

2. Geographic Disparities : Regional institutions show lower average scores

3. Prestige Bias : Top-tier institutions correlate with 15-20% higher scores

5. BIAS DETECTION RESULTS

5.1 Disparate Impact Analysis

Using score thresholds at 0.5 and 0.7 as selection criteria:

Proxy Group	Threshold	Selection Rate	DIR	Below 80%?
Regional vs Metro Institutions	0.5	75% vs 85%	0.88	No
Regional vs Metro Institutions	0.7	35% vs 48%	0.73	Yes
Non-technical vs Technical Skills	0.5	68% vs 83%	0.82	No
Non-technical vs Technical Skills	0.7	28% vs 45%	0.62	Yes

5.2 Demographic Parity Testing

Significant differences in score distributions suggest violation of demographic parity:

- Institution-based DPD: 0.13 at 0.7 threshold
- Skills-based DPD: 0.17 at 0.7 threshold

5.3 Regression Analysis

Multivariate regression reveals:

Score = 0.42 + 0.15(Technical_Skills) + 0.08(Elite_Institution) + 0.12(Years_Experience) − 0.05(Non_Metro) + ε

R^2 = 0.31, indicating substantial unexplained variance potentially attributable to bias.

6. IMPLICATIONS AND RECOMMENDATIONS

6.1 Legal Compliance Requirements

Organizations using AI recruitment tools must:

1. Conduct annual bias audits per NYC Local Law 144

2. Maintain disparate impact ratios above 80% threshold

3. Provide alternative selection processes

4. Document bias testing methodologies

6.2 Technical Mitigation Strategies

Pre-processing: Reweight training data to balance representation

In-processing: Incorporate fairness constraints in model optimization

Post-processing: Adjust thresholds to achieve demographic parity

6.3 Organizational Best Practices

1. Implement continuous monitoring with monthly disparate impact calculations

2. Establish cross-functional AI governance committees

3. Require vendor bias audit reports before procurement

4. Maintain human oversight in final hiring decisions

7. CONCLUSIONS

This empirical analysis of 9,544 resume-job matches reveals significant evidence of algorithmic bias in AI recruitment tools. Disparate impact ratios falling below the 80% threshold for certain proxy groups, combined with substantial score variations across job categories, indicate systematic discrimination patterns.

The mean matching score of 0.661 with high variance ($\sigma = 0.167$) suggests inconsistent evaluation criteria that may encode historical biases. Technical roles show consistently higher scores than non-technical positions, potentially reflecting gender and educational background biases embedded in training data.

Organizations must implement comprehensive bias testing frameworks, combining technical solutions with governance structures to ensure fair and equitable AI-driven recruitment. As legal frameworks continue to evolve, proactive bias mitigation becomes not just an ethical imperative but a compliance requirement.

Future research should focus on developing more sophisticated proxy variables for demographic inference while respecting privacy, testing bias mitigation techniques in production environments, and establishing industry-standard benchmarks for acceptable bias levels in recruitment AI.

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