

Algorithmic Bias in Recruitment: Examining Artificial Intelligence and Women's Right to Equal Employment

Author: Afzal Ahamad

Research scholar, Department of Political Science & Human Rights.
Jamia Hamdard, New Delhi.

Co-author: Prof. (Dr) Syed Mehartaj Begum

Head, Department of Political Science & Human Rights.
Dean, School of Humanities and Social Sciences
Jamia Hamdard, New Delhi.

Abstract

The increasing use of artificial intelligence (AI) in recruitment has raised concerns regarding algorithmic bias, gender discrimination, and women's right to equal employment. This study examines the relationships between AI-enabled recruitment practices, perceived AI discrimination, recruitment fairness, and anti-discrimination policies. A quantitative, cross-sectional research design was adopted using survey data from 237 respondents representing diverse demographic and professional backgrounds. Reliability analysis, exploratory factor analysis, and multiple regression analysis were conducted using R software. The findings indicate that algorithmic bias and gender stereotyping are positively associated with perceived AI discrimination, whereas AI transparency demonstrates a significant negative association. Accuracy of AI screening and gender-neutral recruitment are positively associated with recruitment fairness, while perceived AI discrimination exhibits a negative association. Furthermore, AI accountability and HR professional awareness are positively associated with anti-discrimination policies. The study highlights the importance of transparent, accountable, and gender-sensitive AI recruitment practices in promoting fair employment opportunities. The findings offer practical implications for responsible AI implementation in human resource management.

Keywords: Algorithmic Bias, Artificial Intelligence, Gender Equality, Recruitment Fairness

1. Introduction

Artificial intelligence (AI) is increasingly transforming recruitment and human resource management by automating activities such as résumé screening, candidate ranking, interview assessment, skills evaluation, and employee selection. These technologies are widely adopted because they can process large volumes of applications, reduce administrative workloads, and support faster recruitment decisions. However, the growing reliance on algorithmic decision-making has raised important questions concerning fairness, transparency, accountability, and gender equality in employment. Although AI-based recruitment systems are frequently presented as objective alternatives to human judgment, their decisions may reproduce or intensify existing social inequalities when the data,

assumptions, and evaluation criteria used to develop them reflect historical patterns of discrimination. Consequently, understanding algorithmic bias has become essential for assessing whether AI-supported recruitment practices protect or undermine women's right to equal employment opportunities (Albaroudi et al., 2024; Capasso et al., 2024; Hall & Ellis, 2023).

Women's right to equal employment encompasses fair access to recruitment, selection, promotion, and professional development without discrimination based on gender. Nevertheless, gender-based inequalities may persist through organizational practices, occupational segregation, unequal access to leadership positions, and assumptions regarding women's professional capabilities and career commitments. When recruitment algorithms are trained on historical employment records, they may learn patterns reflecting these existing inequalities. For example, if a company's historical workforce is predominantly male in senior technical or managerial positions, an algorithm trained on previous hiring decisions may associate male-dominated career trajectories with successful candidates. Similarly, employment gaps, career interruptions, educational backgrounds, and language patterns may become indirect indicators that disadvantage women. Such outcomes demonstrate that removing explicit gender information from an algorithm does not necessarily eliminate discrimination because other variables may function as proxies for gender (Liu & Murphy, 2022; Lütz, 2022; Pethig & Kroenung, 2023).

Algorithmic bias in recruitment can emerge at several stages, including data collection, model development, feature selection, system implementation, and organizational interpretation of algorithmic recommendations. Biased or unrepresentative training datasets may lead AI systems to evaluate candidates according to patterns that do not adequately represent diverse professional experiences. Furthermore, automated résumé-screening systems may assign different scores to candidates with comparable qualifications because of differences in career histories, wording, or other characteristics associated with gender. AI-enabled video interviews and assessment tools may also create concerns regarding the reliability and fairness of automated evaluations across different candidate groups. The consequences extend beyond individual rejection: repeated biased decisions can restrict women's access to employment, reinforce occupational segregation, and reproduce gender inequalities across organizational hierarchies. These concerns make it necessary to examine algorithmic recruitment not simply as a technological innovation but also as a socio-

organizational process with significant implications for employment rights (Jablan et al., 2024; Mushtaq et al., 2025; Oliveira et al., 2025).

An important challenge is that algorithmic discrimination may remain difficult to identify because automated decisions are often complex, technically sophisticated, or insufficiently transparent to applicants and other stakeholders. Organizations may assume that standardized algorithms necessarily produce more consistent and impartial decisions than human recruiters. However, consistency does not automatically establish fairness, particularly when the underlying data or decision criteria are systematically disadvantageous to women. Limited explanations of candidate rankings can also make it difficult to determine why an applicant was rejected or whether gender-related factors influenced the outcome. In this context, transparency, explainability, independent auditing, and meaningful human oversight are important considerations in evaluating the legitimacy of AI-based recruitment systems. Researchers and organizations must therefore distinguish between the efficiency of automated recruitment and its capacity to deliver equitable outcomes (Schulte Steinberg & Hohenberger, 2023; Zafonte & Cerquitelli, 2026).

The relationship between AI and women's employment rights also requires attention to organizational accountability and regulatory safeguards. Fair recruitment cannot be achieved solely by removing sensitive personal attributes from datasets or relying on the technical performance of an algorithm. It requires systematic examination of training data, selection criteria, model outputs, and differences in recruitment outcomes across gender groups. Organizations must also establish clear responsibilities for reviewing automated recommendations, responding to discrimination complaints, and correcting identified biases. Human involvement is particularly important when algorithmic recommendations influence decisions with substantial consequences for applicants' economic independence and professional opportunities. Research examining AI governance, employment discrimination, and responsible technological implementation can contribute to developing recruitment practices that balance operational efficiency with equality, fairness, and accountability (Guedes et al., 2025; Gümrükçüoğlu & Kutsal, 2025; Ip, 2025).

Despite increasing scholarly attention to algorithmic decision-making, the issue remains multidimensional because technological design, organizational practices, gender relations, and legal protections interact in shaping recruitment outcomes. The literature identified for this study provides a basis for examining these connected dimensions, including the

emergence of algorithmic bias, the implications of automated decision-making for women, and the mechanisms required to promote fair employment practices. Further investigation is important to understand whether AI-supported recruitment systems improve procedural consistency while simultaneously creating less visible barriers to equal opportunity. It is also necessary to consider how organizations can identify discriminatory outcomes and implement safeguards that protect women's access to employment throughout the recruitment process (Arora & Gupta, 2026; Ertürk & Ayhan, 2026; Kelan, 2026; Shah et al., 2026).

Accordingly, the present study, titled “Algorithmic Bias in Recruitment: Examining Artificial Intelligence and Women’s Right to Equal Employment,” examines the implications of AI-based recruitment for gender equality and women’s employment rights. It focuses on understanding the potential sources and consequences of algorithmic bias, evaluating the fairness of automated recruitment practices, and identifying the importance of transparency, accountability, and human oversight. By connecting technological decision-making with the broader principle of equal employment opportunity, the study seeks to contribute to discussions on responsible AI adoption in human resource management. Its central concern is that recruitment technologies should not merely accelerate hiring decisions but should also support fair assessment and equitable access to employment. Ensuring that AI systems are designed, evaluated, and monitored with gender equality in mind is therefore essential to making technological progress compatible with women’s right to equal employment.

2. Literature Review and Hypothesis Development

2.1. Artificial Intelligence and Algorithmic Bias in Recruitment

Artificial intelligence has become an important component of contemporary recruitment, supporting résumé screening, candidate ranking, applicant assessment, and employment decision-making. These applications can improve processing speed and standardize recruitment procedures; however, their contribution to fair employment depends on the quality of the data, the criteria used to evaluate candidates, and the governance mechanisms established by organizations. Algorithmic systems are not inherently free from discrimination because their predictions may reflect patterns embedded in historical recruitment decisions and organizational practices. Consequently, AI-based recruitment requires evaluation not only in terms of operational efficiency but also in relation to fairness,

transparency, and equal access to employment (Albaroudi et al., 2024; Capasso et al., 2024; Hall & Ellis, 2023).

Gender-based algorithmic bias is particularly important because historical employment data may reflect unequal representation, occupational segregation, and established stereotypes concerning professional suitability. When these patterns influence model development, automated systems may reproduce existing disadvantages even when gender is not explicitly included as a decision-making variable. Characteristics such as career interruptions, previous employment patterns, and educational or professional trajectories may indirectly influence candidate rankings. Therefore, algorithmic recruitment should be examined as a socio-technical process in which technological design interacts with existing organizational and social inequalities (Liu & Murphy, 2022; Lütz, 2022; Pethig & Kroenung, 2023).

The implications of algorithmic bias extend beyond individual recruitment decisions. If women consistently receive lower rankings or fewer opportunities because of biased evaluation criteria, AI-supported recruitment may reinforce occupational inequality and restrict access to economic independence and career advancement. Assessing the relationship between algorithmic recruitment practices and perceived discrimination is therefore necessary for understanding whether technological adoption supports or undermines women's right to equal employment (Jablan et al., 2024; Mushtaq et al., 2025; Oliveira et al., 2025).

2.2. AI Recruitment Practices and Perceived Algorithmic Discrimination

Perceived algorithmic discrimination represents an important dimension of recruitment fairness because applicants and recruitment professionals may evaluate whether automated decisions treat candidates consistently and equitably. Such perceptions can be influenced by the design and operation of AI systems, the transparency of decision criteria, the representation of different groups in training data, and the availability of human review. Although automation may reduce certain forms of inconsistency in human decision-making, it does not necessarily eliminate discriminatory outcomes. A system can apply the same procedure to every applicant and still produce unequal results when its underlying criteria disadvantage particular groups (Ertürk & Ayhan, 2026; García, 2025; Guedes et al., 2025).

The perceived fairness of AI-supported recruitment is also associated with the extent to which candidates can understand how their applications are assessed. When organizations cannot explain why an algorithm ranks one candidate above another, applicants may find it difficult to evaluate the legitimacy of the decision. Transparent procedures, appropriate communication, and opportunities for human review can help organizations identify questionable outcomes and strengthen accountability. Conversely, weak oversight may allow problematic decision rules to continue without sufficient examination (Ip, 2025; Pisanelli, 2022, 2026; Zafonte & Cerquitelli, 2026).

In the present study, the relationships between ABR, AIT, GSA, HOR, and PAD provide an empirical basis for examining how recruitment-related factors are associated with perceived algorithmic discrimination. These relationships are important because they connect the broader debate on AI and gender equality with measurable perceptions of recruitment practices. However, the expected direction of each relationship depends on the precise operational definitions of the constructs and the wording of the measurement items. Accordingly, the hypotheses below follow the predictor–outcome structure of the study's regression model, while their interpretation should remain consistent with the questionnaire definitions.

H1: ABR has a significant relationship with PAD.

H2: AIT has a significant relationship with PAD.

H3: GSA has a significant relationship with PAD.

H4: HOR has a significant relationship with PAD.

2.3. Gender Equality, Recruitment Fairness, and Women's Employment Rights

Women's right to equal employment requires that recruitment decisions be based on relevant qualifications, competencies, and job-related criteria rather than gender-based assumptions. AI-supported recruitment creates opportunities to standardize assessment, but the achievement of gender equality depends on whether these systems identify and prevent discriminatory patterns. If automated decision-making reproduces historical disadvantages, technological efficiency may coexist with unequal employment outcomes. Therefore, recruitment fairness should be evaluated in terms of both procedural consistency and the

substantive consequences of algorithmic decisions for women (Ayata, 2026; Barqawi & Al-Rashdan, 2025; Espinoza-Escobar, 2025).

A further consideration is the role of gender-related assumptions in determining candidate suitability. Algorithms may learn from historical recruitment outcomes in which particular professional roles were disproportionately associated with men. Such associations can influence the assessment of qualifications and experience, potentially restricting women's access to opportunities in male-dominated occupations. Addressing these risks requires organizations to review the relevance of selection criteria, assess outcomes across gender groups, and ensure that automated recommendations remain subject to meaningful scrutiny. The protection of women's employment rights consequently requires more than technical accuracy; it also requires organizational commitment to equality and non-discrimination (Kelan, 2026; Khurana et al., 2026; Robertson Nogues, 2026).

The relationship between AAS, GNR, PAD, and FAR provides another empirical dimension of the present study. Examining these constructs together allows the analysis to investigate whether the selected recruitment-related factors are associated with the study's fairness-related outcome. This relationship is particularly relevant because perceptions of fairness may depend on how recruitment procedures are designed, how gender-related concerns are addressed, and whether potentially discriminatory outcomes are recognized. Nevertheless, the interpretation of these relationships must be grounded in the actual questionnaire items rather than inferred solely from construct abbreviations.

Accordingly, the following hypotheses are proposed:

H5: AAS has a significant relationship with FAR.

H6: GNR has a significant relationship with FAR.

H7: PAD has a significant relationship with FAR.

2.4. Accountability, Data Protection, and Responsible AI Recruitment

Responsible AI adoption requires organizations to establish governance mechanisms that address the ethical and practical implications of automated employment decisions. These mechanisms may include reviewing algorithmic outputs, assessing potential bias,

maintaining appropriate records, communicating the role of AI in selection, and providing channels for applicants to question recruitment decisions. Such measures are important because responsibility for an algorithmic decision cannot be separated entirely from the organization that selects, deploys, and relies on the system. Human resource professionals and organizational leaders therefore have an important role in ensuring that automated recruitment remains compatible with fairness and equal employment principles (Arora & Gupta, 2026; Parviainen, 2026; Shah et al., 2026).

Data protection is another significant consideration. AI recruitment systems may process personal information, employment histories, qualifications, assessment results, and other candidate characteristics. Inappropriate data collection, inadequate safeguards, or the use of irrelevant information may undermine trust and create additional risks for applicants. Organizations must therefore consider how candidate information is collected, processed, stored, and used in recruitment decisions. Data governance should be accompanied by clear responsibility for reviewing the consequences of algorithmic decisions, particularly when those decisions affect access to employment (Ebbage, 2020; Joseph & Mandla, 2024; Sivakaminathan & Musi, 2026).

The broader challenge is to ensure that technological implementation does not weaken organizational accountability. Even when AI systems provide recommendations efficiently, recruitment professionals should retain the capacity to evaluate their relevance, question potentially problematic outcomes, and consider information that automated systems may overlook. Such oversight is particularly important when algorithmic recommendations have implications for gender equality. Responsible implementation must therefore combine technological capabilities with appropriate organizational controls and attention to the rights of affected applicants (Antonopoulou, 2023; Capasso et al., 2024; Hughes et al., 2026).

In this study, AIA, DPP, and HRP are examined in relation to ADP. This model provides an opportunity to investigate whether the three specified factors are associated with the study's final outcome. The relationships are relevant to the wider discussion of accountable AI because responsible recruitment involves both the technical management of automated systems and the organizational capacity to identify and respond to potentially discriminatory practices. However, the exact conceptual meaning of each relationship should be established using the definitions and items in the questionnaire.

The following hypotheses are therefore proposed:

H8: AIA has a significant relationship with ADP.

H9: DPP has a significant relationship with ADP.

H10: HRPD has a significant relationship with ADP.

2.5. Research Gap and Conceptual Contribution

The literature on AI-supported recruitment raises interconnected concerns regarding algorithmic bias, gender stereotypes, recruitment fairness, transparency, data protection, and organizational accountability. These issues demonstrate that AI adoption cannot be assessed exclusively through its ability to accelerate recruitment or standardize candidate evaluation. Its broader significance lies in whether automated systems support equitable employment opportunities or reproduce existing disadvantages. Research addressing these dimensions is important for connecting technological innovation with women's right to equal employment (Gümrükçüoğlu & Kutsal, 2025; Pathak et al., 2024; Pisanelli, 2026).

A relevant research gap concerns the need to examine multiple recruitment-related factors and outcomes within a common empirical framework. Studying these dimensions separately may not fully explain how perceptions of algorithmic discrimination, recruitment fairness, and other responsible-AI-related outcomes relate to the factors specified in the research model. The present study addresses this issue by examining three regression relationships: ABR, AIT, GSA, and HOR in relation to PAD; AAS, GNR, and PAD in relation to FAR; and AIA, DPP, and HRPD in relation to ADP. These models provide a structured basis for assessing the proposed associations using the survey responses.

The study contributes to the discussion of gender equality by examining perceptions associated with AI-enabled recruitment rather than assuming that automated systems are inherently fair or discriminatory. Its findings may help identify which measured factors are significantly associated with the selected outcomes and may inform further investigation of responsible recruitment practices. However, because the analysis uses survey-based measures, the findings should be interpreted as evidence of statistical associations rather than definitive proof that AI systems cause discrimination or violate women's employment rights.

3. Research Methodology

3.1. Research Design and Sample

The study follows a cross-sectional, survey-based research design. The dataset comprises 237 respondents with diverse demographic and professional backgrounds, including HR and recruitment professionals, job seekers, students, and employed individuals. The collected demographic information includes gender, age group, educational qualification, employment status, work experience, organizational sector, and familiarity with AI. These characteristics provide contextual information for understanding respondents' perceptions of AI-based recruitment practices. The available dataset does not independently establish the sampling technique or geographical coverage; therefore, these details should be specified only when supported by the original data-collection records.

3.2. Measurement and Instrument Development

Data were organized using a structured questionnaire containing 36 measurement items distributed across 12 constructs, with three items assigned to each construct. The constructs were coded as ABR, AIT, GSA, HOR, FAR, AAS, GNR, PAD, AIA, DPP, ADP, and HRP. The questionnaire responses were analyzed using construct-level scores derived from the corresponding measurement items. The precise wording of the questionnaire items and the response-scale anchors should be reported according to the original instrument to ensure measurement transparency and reproducibility.

3.3. Statistical Analysis

The analysis was conducted using R software. Descriptive statistics were used to summarize respondents' demographic characteristics. Internal consistency was assessed using Cronbach's alpha, while the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity were used to examine the suitability of the measurement data for factor analysis. Exploratory factor analysis was performed to investigate the underlying factor structure. Multiple regression analysis was then used to examine three proposed models: ABR, AIT, GSA, and HOR predicting PAD; AAS, GNR, and PAD predicting FAR; and AIA, DPP, and HRP predicting ADP. Variance inflation factors were examined for multicollinearity, the Breusch–Pagan test was used to assess heteroscedasticity, and HC3 heteroscedasticity-robust standard errors were calculated for additional inference. Statistical significance was

evaluated using the reported regression p-values. The cross-sectional design supports the assessment of associations but does not establish causal relationships.

4. Results

The demographic profile presents the characteristics of 237 respondents. Regarding gender, women constituted the largest group, with 125 respondents (52.74%), followed by men at 45.99%. Most respondents were aged 25–34 years (38.40%), followed by those aged 35–44 years (28.27%). In terms of education, postgraduates represented the largest category (48.52%), indicating a relatively well-educated sample. Employment status varied, with employed respondents accounting for 26.16%, followed by job seekers (23.63%) and HR/recruitment professionals (21.10%). Regarding work experience, 34.18% had 1–5 years of experience, while 27.43% reported no work experience. Most respondents worked in the private sector (52.74%). Concerning AI familiarity, nearly half reported moderate familiarity (49.37%), followed by high familiarity (28.27%). Overall, the sample includes diverse professional backgrounds and varying levels of AI familiarity, providing a useful basis for examining perceptions of AI-based recruitment.

Table 1. Reliability Analysis

Construct	Number of items	Cronbach's alpha	Standardized alpha
Algorithmic Bias in Recruitment (ABR)	3	0.713	0.713
AI Transparency (AIT)	3	0.727	0.728
Gender Stereotyping in Algorithms (GSA)	3	0.728	0.728
Human Oversight in Recruitment (HOR)	3	0.727	0.726
Fairness of AI Recruitment (FAR)	3	0.707	0.707
Accuracy of AI Screening (AAS)	3	0.741	0.743
Gender-Neutral Recruitment (GNR)	3	0.685	0.684
Perceived AI Discrimination (PAD)	3	0.732	0.732
AI Accountability (AIA)	3	0.722	0.722
Data Privacy Protection (DPP)	3	0.729	0.729
Anti-Discrimination Policies (ADP)	3	0.745	0.745
HR Professional Awareness (HRPA)	3	0.739	0.740

Table 1 presents the internal consistency of the 12 constructs measured in the study, with three items used for each construct. Cronbach's alpha values range from 0.685 to 0.745, indicating generally acceptable reliability for exploratory research. Anti-Discrimination Policies (ADP) records the highest alpha value of 0.745, followed by Accuracy of AI Screening (AAS) at 0.741 and HR Professional Awareness (HRPA) at 0.739. AI Transparency (AIT), Gender Stereotyping in Algorithms (GSA), Human Oversight in Recruitment (HOR), and Data Privacy Protection (DPP) also demonstrate satisfactory

internal consistency. Gender-Neutral Recruitment (GNR) records the lowest alpha of 0.685, which is slightly below the commonly used 0.70 benchmark and may warrant further examination. Overall, the reliability results suggest that the constructs are sufficiently consistent for preliminary analysis, although GNR should be interpreted with some caution.

Table 2. KMO and Bartlett's Test

Test	Statistic	Result
Kaiser–Meyer–Olkin (KMO)	0.762	Acceptable
Bartlett's test of sphericity: Chi-square	2637.653	Significant
Degrees of freedom	630	—
p-value	Below 0.001	Significant

Table 2 evaluates whether the dataset is suitable for exploratory factor analysis (EFA). The Kaiser–Meyer–Olkin (KMO) value is 0.762, exceeding the commonly accepted minimum of 0.60 and indicating adequate sampling adequacy for identifying underlying factor structures. Bartlett's test of sphericity is statistically significant, with a chi-square value of 2637.653, 630 degrees of freedom, and a p-value below 0.001. This result indicates that the correlation matrix differs significantly from an identity matrix, suggesting that the measured variables share sufficient correlations for factor analysis. Taken together, the KMO and Bartlett's test results support proceeding with EFA to examine the relationships among the questionnaire items. However, these tests establish the suitability of the correlation structure for factor analysis; they do not independently confirm the validity of the proposed constructs or the final factor structure.

Table 3. EFA Model Fit and Explained Variance

Measure	Result
Number of factors extracted	12
Total variance explained by 12 factors	46.6%
Tucker–Lewis Index (TLI)	0.991
RMSEA	0.010
RMSEA lower confidence limit	0.000
RMSEA upper confidence limit	0.028
RMSR	0.021

Table 3 presents the factor structure and model-fit statistics obtained from exploratory factor analysis. The analysis extracted 12 factors, which collectively explain 46.6% of the total variance in the measured items. The Tucker–Lewis Index (TLI) is 0.991, indicating a strong fit according to commonly used fit criteria. The Root Mean Square Error of Approximation

(RMSEA) is 0.010, with a confidence interval ranging from 0.000 to 0.028, while the Root Mean Square Residual (RMSR) is 0.021. These values suggest that the estimated factor model reproduces the observed correlation structure relatively well. Nevertheless, the total variance explained is moderate, and the extraction of 12 factors should be theoretically justified because the study includes 12 proposed constructs. The factor solution should also be assessed against the parallel-analysis results and the item-loading pattern before concluding that the measurement structure is fully supported.

Table 4: Regression Results: Algorithmic Bias in Recruitment

	<i>Dependent variable:</i>		
	Perceived AI Discrimination	Recruitment Fairness	Anti-Discrimination Policies
	Model 1: AI Discrimination	Model 2: Recruitment Fairness	Model 3: Anti-Discrimination Policies
	(1)	(2)	(3)
ABR_Mean	0.251*** t = 4.312		
AIT_Mean	-0.153** t = -2.797		
GSA_Mean	0.284*** t = 4.614		
HOR_Mean	-0.094 t = -1.623		
AAS_Mean		0.188** t = 3.232	
GNR_Mean		0.332*** t = 5.320	
PAD_Mean		-0.182** t = -2.967	
AIA_Mean			0.281*** t = 4.395
DPP_Mean			0.124 t = 1.924
HRPA_Mean			0.195** t = 3.276
Constant	2.105*** t = 6.473	2.043*** t = 6.374	1.168*** t = 4.569
Observations	237	237	237
Adjusted R-squared	0.193	0.189	0.19

F-statistic	15.075	19.344	19.496
Observations	237	237	237
R ²	0.206	0.199	0.201
Adjusted R ²	0.193	0.189	0.190
F Statistic	15.075*** (df = 4; 232)	19.344*** (df = 3; 233)	19.496*** (df = 3; 233)

Note: *p<0.05; **p<0.01; ***p<0.001

Table 4 reports three regression models based on 237 observations. In Model 1, Algorithmic Bias in Recruitment (ABR) and Gender Stereotyping in Algorithms (GSA) are positively associated with Perceived AI Discrimination, with coefficients of 0.251 and 0.284, respectively. AI Transparency (AIT) has a significant negative coefficient of -0.153, while Human Oversight in Recruitment (HOR) is not statistically significant. Model 1 explains 20.6% of the variance in perceived discrimination. In Model 2, Accuracy of AI Screening (AAS) and Gender-Neutral Recruitment (GNR) are positively associated with Recruitment Fairness, whereas Perceived AI Discrimination (PAD) has a negative association. The model explains 19.9% of the variance. In Model 3, AI Accountability (AIA) and HR Professional Awareness (HRPA) are positively associated with Anti-Discrimination Policies (ADP), while Data Privacy Protection (DPP) is not significant at the 5% level. The model explains 20.1% of the variance. These findings indicate meaningful associations, but interpretation of positive coefficients depends on how each construct is coded and measured.

4. Discussion

The findings provide insights into the relationship between artificial intelligence (AI)-enabled recruitment practices, perceived discrimination, recruitment fairness, and anti-discrimination policies. The reliability analysis indicates that most constructs demonstrate acceptable internal consistency, although Gender-Neutral Recruitment records a Cronbach's alpha of 0.685, suggesting scope for further refinement. The KMO value of 0.762 and significant Bartlett's test support the suitability of the data for exploratory factor analysis. These findings provide a preliminary measurement foundation for examining algorithmic bias in recruitment.

The first regression model indicates that Algorithmic Bias in Recruitment and Gender Stereotyping in Algorithms are positively associated with Perceived AI Discrimination. These findings suggest that respondents who report stronger algorithmic bias and gender-stereotyping concerns also tend to report greater perceived discrimination. AI Transparency

demonstrates a significant negative association, indicating that greater transparency may be associated with lower perceived discrimination. However, Human Oversight in Recruitment is not statistically significant, suggesting that oversight alone may not be sufficient to explain differences in perceived discrimination. These findings are consistent with concerns regarding the reproduction of historical inequalities through automated decision-making (Liu & Murphy, 2022; Pethig & Kroenung, 2023).

The second model reveals positive associations between Accuracy of AI Screening, Gender-Neutral Recruitment, and Recruitment Fairness, whereas Perceived AI Discrimination has a negative association with fairness. This highlights the importance of reliable screening procedures and gender-neutral evaluation criteria. The third model identifies positive associations between AI Accountability, HR Professional Awareness, and Anti-Discrimination Policies. Data Privacy Protection, however, is not statistically significant at the 5% level. These results emphasize the potential importance of accountability, professional awareness, and transparent recruitment procedures in responsible AI implementation (Guedes et al., 2025; Ip, 2025; Zafonte & Cerquitelli, 2026). Overall, the models explain approximately 19.9%–20.6% of the variance in their respective outcomes. The findings support further investigation of responsible recruitment practices, although the cross-sectional design establishes associations rather than causal relationships.

5. Conclusion

This study examined algorithmic bias in recruitment and its implications for women's right to equal employment using survey data from 237 respondents. The findings demonstrate that AI-related recruitment factors are associated with perceived discrimination, recruitment fairness, and anti-discrimination policies. The results highlight the importance of evaluating AI systems not only according to operational efficiency but also according to their potential implications for equality and non-discrimination in employment.

The regression analysis identifies positive associations between algorithmic bias, gender stereotyping, and perceived AI discrimination. AI transparency is negatively associated with perceived discrimination, while human oversight does not demonstrate a statistically significant relationship in the first model. In the second model, accuracy of AI screening and gender-neutral recruitment are positively associated with recruitment fairness, whereas perceived discrimination is negatively associated with fairness. In the third model, AI

accountability and HR professional awareness are positively associated with anti-discrimination policies. Data privacy protection is not statistically significant at the conventional 5% level. These findings reinforce the importance of transparency, gender-sensitive evaluation, and organizational accountability in AI-supported recruitment (Capasso et al., 2024; Gümrükçüoğlu & Kutsal, 2025; Kelan, 2026).

The study has practical implications for organizations using automated recruitment systems. Employers should regularly evaluate algorithmic outcomes, examine potential gender disparities, establish clear accountability procedures, and ensure that applicants have appropriate opportunities for review. HR professionals should also receive training to identify algorithmic limitations and interpret automated recommendations critically. These measures may help organizations develop more responsible recruitment practices and strengthen equal employment opportunities (Jablan et al., 2024; Mushtaq et al., 2025).

Despite these contributions, the study is limited by its cross-sectional design, reliance on respondents' perceptions, and moderate explanatory power of the regression models. Future research could use larger and more diverse samples, compare recruitment outcomes across gender groups, and examine actual hiring decisions alongside survey responses. Longitudinal studies and algorithmic audits could further investigate whether transparency, accountability, and human oversight reduce discriminatory outcomes over time. Such research would strengthen understanding of how AI can be implemented in ways that protect women's employment rights and promote equitable recruitment.

7. References

- [1] Albaroudi, E., Mansouri, T., & Alameer, A. (2024). A Comprehensive Review of AI Techniques for Addressing Algorithmic Bias in Job Hiring. *AI (Switzerland)*, 5(1), 383–404. <https://doi.org/10.3390/ai5010019>
- [2] Antonopoulou, C. (2023). Algorithmic bias in anthropomorphic artificial intelligence: Critical perspectives through the practice of women media artists and designers. *Technoetic Arts*, 21(2), 157–174. https://doi.org/10.1386/tear_00109_1
- [3] Arora, A. A., & Gupta, C. (2026). Women in the Future Driven by AI: Using Generative AI to Create Inclusive Systems. *Lecture Notes in Networks and Systems*, 1744 LNNS, 146–158. https://doi.org/10.1007/978-3-032-12996-3_14
- [4] Ayata, Z. (2026). Gender Bias in AI Systems: A Critical Analysis of Regulatory Frameworks and Policy Responses. *Bialostockie Studia Prawnicze*, 31(1), 135–153. <https://doi.org/10.15290/bsp.2026.31.01.08>
- [5] Barqawi, L., & Al-Rashdan, S. (2025). The Impact of AI on Women's Roles in the Workplace: A Legal Gender Perspective. *Proceeding - 12th International Conference on Information Technology: Innovation Technologies, ICIT 2025*, 631–634. <https://doi.org/10.1109/ICIT64950.2025.11049127>
- [6] Capasso, M., Arora, P., Sharma, D., & Tacconi, C. (2024). On the Right to Work in the

- Age of Artificial Intelligence: Ethical Safeguards in Algorithmic Human Resource Management. *Business and Human Rights Journal*, 9(3), 346–360. <https://doi.org/10.1017/bhj.2024.26>
- [7] Ebbage, A. (2020). LET AI DECIDE? *Engineering and Technology*, 15(2), 38–41. <https://doi.org/10.1049/et.2020.0204>
- [8] Ertürk, M., & Ayhan, E. (2026). Between Efficiency and Fairness: Algorithmic Discrimination in AI-Based Recruitment Systems. In *Employee-AI Experience in Human Resource Management* (pp. 127–157). <https://doi.org/10.4018/979-8-2600-2303-7.ch005>
- [9] Espinoza-Escobar, J. H. (2025). Key elements for the regulation of algorithmic discrimination in the peruvian legal framework. *Ius et Praxis*, 31(2), 163–183. <https://doi.org/10.4067/S0718-00122025000200163>
- [10] García, R. G.-P. (2025). [ENG] Artificial Intelligence Biases in the Double Employment Discrimination of Women on Religious Grounds. *Vergentis*, 21, 41–84. <https://doi.org/10.12800/vg.21.3>
- [11] Guedes, M. J., Rodrigues, R., & Macedo, D. (2025). AI and Gender Equality: One Step Forward or Two Steps Back? *Proceedings of the International Conference on Gender Research*, 141–149. <https://doi.org/10.34190/icgr.8.1.3483>
- [12] Gümrükçüoğlu, Y. B., & Kutsal, F. B. S. (2025). Algorithmic discrimination against women in the recruitment process. In *Digitalization and Women's Rights: Volume I* (Vol. 1, pp. 278–292). <https://doi.org/10.1201/9781003507031-20>
- [13] Hall, P., & Ellis, D. (2023). A systematic review of socio-technical gender bias in AI algorithms. *Online Information Review*, 47(7), 1264–1279. <https://doi.org/10.1108/OIR-08-2021-0452>
- [14] Hughes, K. D., Konnikov, A., Denier, N., & Hu, Y. (2026). Problematizing the role of artificial intelligence in hiring and organizational inequalities: A multidisciplinary review. *Human Relations*, 79(2 Inaugural Special Issue: Critical Reviews), 246–278. <https://doi.org/10.1177/00187267251403902>
- [15] Ip, E. (2025). Fair AI in hiring: Experimental evidence on how biased hiring algorithms and different debiasing methods affect the quality and diversity of applicants. *Behavioral Science and Policy*, 11(1), 44–54. <https://doi.org/10.1177/23794607251353585>
- [16] Jablan, J., Lakovic, L., & Micanovic, A. (2024). Algorithmic Discrimination: Continuation of Human Bias or a Gateway to Equality? *2024 28th International Conference on Information Technology, IT 2024*. <https://doi.org/10.1109/IT61232.2024.10475756>
- [17] Joseph, V., & Mandla, V. R. (2024). CODED DISCRIMINATION: GENDER BLINDSPOTS IN ARTIFICIAL INTELLIGENCE. *Journal of Rural Development*, 43(4), 461–471. <https://doi.org/10.25175/jrd/2024/v43/i4/173424>
- [18] Kelan, E. K. (2026). Negotiating algorithmic bias: discourses of techno-optimism and techno-hesitation in AI-mediated hiring. *Information Technology and People*, 1–18. <https://doi.org/10.1108/ITP-03-2025-0370>
- [19] Khurana, D. S., Parbhakar, D., & Kaur, R. (2026). Regulating Algorithmic Bias and Global Legal Approaches in Gender, Diversity, and Intersectional Equity in AI-Driven Professional Systems. In *Imposter Syndrome and AI: Navigating Human Identity in the Age of Intelligent Machines* (pp. 391–410). <https://doi.org/10.4018/979-8-3373-6618-0.ch020>
- [20] Liu, X. M., & Murphy, D. (2022). Applying a Trustworthy AI Framework to Mitigate Bias and Increase Workforce Gender Diversity. *International Symposium on Technology and Society, Proceedings*, 2022-November. <https://doi.org/10.1109/ISTAS55053.2022.10227119>

- [21] Lütz, F. (2022). Gender equality and artificial intelligence in Europe. Addressing direct and indirect impacts of algorithms on gender-based discrimination. *ERA Forum*, 23(1), 33–52. <https://doi.org/10.1007/s12027-022-00709-6>
- [22] Mushtaq, S., Babar, D., Farah, N., & Rehman, M. (2025). AI and gender inequality: Challenges, opportunities, and pathways to equity. In *Social System Reforms to Achieve Global Sustainability* (pp. 23–42). <https://doi.org/10.4018/979-8-3373-1280-4.ch002>
- [23] Oliveira, A. L., Hernandez-Ramirez, R., & Ayanoglu, H. (2025). AI and Gender Perspectives in Startup Environments: Mitigating Bias, Challenging Stereotypes, and Design Implications. *Lecture Notes in Computer Science*, 15772 LNCS, 396–418. https://doi.org/10.1007/978-3-031-93982-2_26
- [24] Parviainen, H. (2026). Effective remedies for job applicants in algorithmic recruitment: the contribution of the EU Artificial Intelligence Act. *Law, Innovation and Technology*. <https://doi.org/10.1080/17579961.2026.2710954>
- [25] Pathak, S., Solanki, V. K., & Linh, N. T. D. (2024). Gender Biasness – A Victim of Artificial Intelligence-Based Development. In *Signals and Communication Technology: Vol. Part F1803* (pp. 81–98). https://doi.org/10.1007/978-3-031-45237-6_8
- [26] Pethig, F., & Kroenung, J. (2023). Biased Humans, (Un)Biased Algorithms? *Journal of Business Ethics*, 183(3), 637–652. <https://doi.org/10.1007/s10551-022-05071-8>
- [27] Pisanelli, E. (2022). Your resume is your gatekeeper: Automated resume screening as a strategy to reduce gender gaps in hiring. *Economics Letters*, 221. <https://doi.org/10.1016/j.econlet.2022.110892>
- [28] Pisanelli, E. (2026). A Tale of Two: Can Gender Equality and Efficiency Go Hand in Hand? *Italian Economic Journal*, 12(1), 669–684. <https://doi.org/10.1007/s40797-025-00322-9>
- [29] Robertson Nogue, A. (2026). Automating injustice: a critical analysis of AI-assisted recruitment processes from a disability justice perspective. *AI and Society*, 41(4), 2761–2768. <https://doi.org/10.1007/s00146-025-02581-7>
- [30] Schulte Steinberg, A. L., & Hohenberger, C. (2023). Can AI close the gender gap in the job market? Individuals' preferences for AI evaluations. *Computers in Human Behavior Reports*, 10. <https://doi.org/10.1016/j.chbr.2023.100287>
- [31] Shah, S., Doshi, J., Patel, D., Chawda, D., & Bhadane, C. (2026). Ethical Approach Towards Singularity by Reducing Biases in the Field of Hiring Employees. *Lecture Notes in Networks and Systems*, 1761 LNNS, 312–324. https://doi.org/10.1007/978-3-032-13555-1_27
- [32] Sivakaminathan, S. S., & Musi, E. (2026). ChatGPT is a gender bias echo-chamber in HR recruitment: an NLP analysis and framework to uncover the language roots of bias. *AI and Society*, 41(4), 2841–2861. <https://doi.org/10.1007/s00146-025-02564-8>
- [33] Zafonte, F., & Cerquitelli, T. (2026). Artificial intelligence and Women's Work: a Review of evidence. *Proceedings - 2026 IEEE 42nd International Conference on Data Engineering Workshops, ICDEW 2026*, 78–84. <https://doi.org/10.1109/ICDEW71238.2026.00015>