



Algorithmic Bias in AI-Driven Hiring Platforms and Its Intersectional Impact on Social Inequality: A Survey of Job Seekers and Platform Users in the Global South

Abubakar Tayyab¹, Syed Muhammad Ayub Shah²

¹Federal Public Service Commission (FPSC), Pakistan

DOI:	https://doi.org/10.65761/jssp.2025.21
How to Cite:	Tayyab, A., & Shah, S. M. A. (2025). Algorithmic Bias in AI-Driven Hiring Platforms and Its Intersectional Impact on Social Inequality: A Survey of Job Seekers and Platform Users in the Global South. <i>Journal of Social Science Perspectives</i> , 2(2), 8-14. doi.org/10.65761/jssp.2025.21
Running Title:	Algorithmic Bias in AI Hiring and Social Inequality

ARTICLE INFORMATION

*Corresponding to:

Syed Muhammad Ayub Shah Federal Public Service Commission (FPSC), Pakistan
Email: syedayubshah@gmail.com

Keywords:

Algorithmic bias, AI-driven recruitment, Intersectionality, Social inequality, Global South

Article History:

Received: 03-11-2025
Revised: 16-12-2025
Accepted: 22-12-2025
Published: 30-12-2025

ABSTRACT

Background: Artificial intelligence (AI) is increasingly used in recruitment to improve efficiency and automate candidate screening. However, concerns persist that algorithmic bias may reinforce existing social inequalities, particularly among vulnerable populations in the Global South.

Objective: To investigate perceptions of algorithmic bias in AI-driven hiring platforms and examine its intersectional impact on social inequality among job seekers and platform users in the Global South.

Methods: A cross-sectional online survey was conducted among 550 respondents recruited through LinkedIn, Facebook groups, university networks, freelancing forums, and WhatsApp communities. Data were collected using a structured questionnaire assessing perceived algorithmic fairness, experiences of discrimination, trust in AI hiring systems, employment outcomes, and attitudes toward AI governance. Statistical analyses included descriptive statistics, reliability analysis, ANOVA, correlation analysis, multiple regression, and moderation analysis.

Results: Women, respondents from lower socio-economic backgrounds, and individuals with lower educational attainment reported significantly higher perceptions of algorithmic discrimination. Digital literacy and previous exposure to AI technologies were positively associated with trust in AI recruitment systems and perceived fairness. Significant interaction effects among gender, socio-economic status, and education indicated that multiple social disadvantages amplified perceptions of algorithmic bias. Participants also expressed substantial concerns regarding transparency, accountability, and fairness in AI-assisted hiring.

Conclusion: AI-driven recruitment systems may unintentionally reproduce existing social inequalities if fairness safeguards are absent. Transparent algorithms, routine bias auditing, inclusive governance, and equitable AI policies are essential to promote fair hiring practices and equal employment opportunities in increasingly digital labor markets.

INTRODUCTION

Artificial Intelligence (AI) has become one of the most transformative technologies of the twenty-first century, reshaping numerous sectors including healthcare, education, finance, transportation, and human resource management (Mhlanga, 2022; Păvăloaia & Necula, 2023). In recent years, organizations have increasingly adopted AI-driven hiring platforms to streamline recruitment processes, reduce operational costs, and improve decision-making efficiency (Mariani & Vega-Lozada, 2023; Vivek, 2023). These systems utilize machine learning algorithms, natural language processing, and predictive analytics to screen resumes, rank applicants, assess candidate suitability, and automate various stages of recruitment (Ali et al., 2022; Tian et al., 2023). Proponents argue that AI-based hiring systems can enhance recruitment efficiency by processing large volumes of applications quickly and objectively while minimizing human bias and subjectivity (Kassir et al., 2023). Consequently, AI-powered recruitment tools have become increasingly popular among multinational corporations, government agencies, and digital employment platforms worldwide (Albassam, 2023; Kshetri, 2021). Despite the potential benefits of AI-assisted recruitment, growing evidence suggests that algorithmic decision-making systems may unintentionally reproduce and amplify existing social inequalities (Tilmes, 2022). Algorithmic bias occurs when automated systems generate outcomes that systematically disadvantage certain individuals or social groups due to biased training data, flawed model design, or unequal representation within datasets (Ferrara, 2023; Ntoutsis et al., 2020). Since machine learning models are trained using

historical data, they may inherit and perpetuate discriminatory patterns already present in society (Franklin et al., 2024). For example, if previous hiring decisions favored particular genders, ethnicities, educational backgrounds, or socio-economic groups, AI systems trained on such data may learn and replicate these preferences in future recruitment decisions (Kartal, 2022). As a result, concerns have emerged regarding the fairness, transparency, and accountability of AI-driven hiring technologies.

The issue of algorithmic bias has attracted significant scholarly attention in recent years (Kordzadeh & Ghasemaghahi, 2022). Several studies have demonstrated that automated hiring systems can disadvantage women, ethnic minorities, older applicants, and

HIGHLIGHTS	
Research insights	AI recruitment may reproduce social inequalities, with women and socioeconomically disadvantaged job seekers reporting greater perceptions of algorithmic discrimination.
Practical insights	Transparent algorithms, bias auditing, digital literacy, and inclusive safeguards can improve fairness, accountability, and equitable employment opportunities within AI-assisted recruitment.
Industry insights	Employers and technology developers should prioritize transparent AI governance, regular bias assessments, and inclusive recruitment practices to support equitable hiring.



individuals from underrepresented socio-economic backgrounds (Kassir et al., 2023). One of the most widely cited examples involved an AI recruitment tool that reportedly penalized applications containing indicators associated with women because the system had been trained on historical hiring data dominated by male candidates (Chang, 2023; Kassir et al., 2023). Such findings highlight the possibility that AI systems may not eliminate discrimination but instead reinforce existing inequalities in new and less visible ways (Zajko, 2021). Furthermore, the complexity of many machine learning algorithms often makes it difficult for applicants to understand how decisions are made, creating concerns regarding transparency and procedural justice (Sambasivan et al., 2021).

The implications of algorithmic bias are particularly important in the context of the Global South, where social inequalities related to gender, education, income, ethnicity, language, and digital access remain significant (Arora et al., 2023; Chaka, 2022; Kshetri, 2021). Countries across South Asia, Africa, and Latin America are experiencing rapid digital transformation and increasing adoption of online recruitment platforms (Kshetri, 2021). However, disparities in technological infrastructure, digital literacy, and access to educational opportunities may influence how different populations interact with AI-based hiring systems (Kshetri, 2021). Individuals from disadvantaged backgrounds may face compounded barriers when seeking employment through algorithmic recruitment processes, potentially exacerbating existing labor market inequalities (Arora et al., 2023; Tilmes, 2022). Despite these concerns, empirical research examining the lived experiences of job seekers in the Global South remains limited, with most studies focusing primarily on Western countries and developed economies (Kshetri, 2021).

An important theoretical framework for understanding these challenges is intersectionality theory. Intersectionality emphasizes that social identities such as gender, socio-economic status, ethnicity, education, and geographic location interact to produce unique experiences of privilege and disadvantage (Wang et al., 2022). Rather than examining demographic characteristics independently, intersectional approaches recognize that multiple forms of inequality may overlap and reinforce one another (Bambra, 2022; Wang et al., 2022). In the context of AI-driven recruitment, individuals belonging to multiple marginalized groups may face greater risks of algorithmic discrimination than those experiencing only a single dimension of disadvantage (Kassir et al., 2023). Consequently, investigating the intersectional impacts of algorithmic bias is essential for understanding how automated hiring technologies affect diverse populations (Kassir et al., 2023; Wang et al., 2022).

Given the growing use of AI-driven recruitment systems and the limited evidence from developing regions, there is a need for research that examines perceptions of algorithmic fairness, experiences of discrimination, trust in AI hiring systems, and employment outcomes among job seekers in the Global South (Kshetri, 2021; Ochmann et al., 2024). Therefore, the present study aims to investigate the relationship between algorithmic bias and social inequality by exploring how demographic and socio-economic factors influence experiences with AI-assisted hiring platforms (Franklin et al., 2024). The study further seeks to examine whether intersectional identities, particularly the interaction of gender, education, and socio-economic status, shape perceptions of fairness and employment opportunities within digital recruitment environments.

The findings of this research are expected to contribute to the growing literature on ethical artificial intelligence, algorithmic governance, and digital inequality (Ferrara, 2023). By providing empirical evidence from the Global South, the study will help policymakers, employers, and technology developers better understand the social consequences of AI-mediated recruitment systems (Kshetri, 2021). Furthermore, the results may support the development of more transparent, accountable, and inclusive hiring

technologies that promote equitable employment opportunities in increasingly digital labor markets.

METHODOLOGY

Study Area and Population

The target population consisted of job seekers, recent graduates, employed individuals, freelancers, and users of online recruitment platforms residing in Global South countries, with particular focus on Pakistan, India, Bangladesh, and neighboring South Asian regions. Participants were required to be at least 18 years of age and to have prior experience using digital job-search platforms such as LinkedIn, Indeed, Rozee.pk, Mustakbil, Upwork, Fiverr, or other AI-assisted recruitment systems.

Sampling Strategy and Sample Size

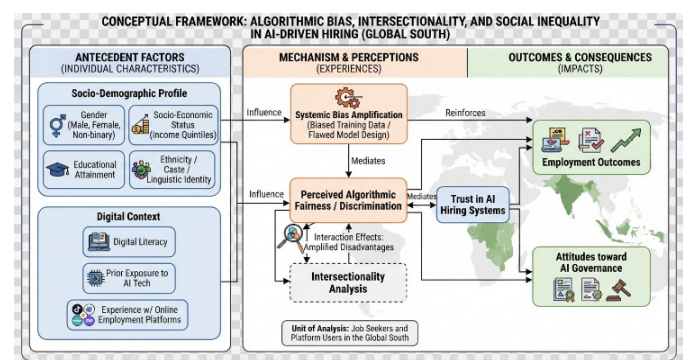
A stratified convenience sampling approach combined with snowball sampling was used to recruit participants through online channels. Recruitment advertisements and survey links were distributed through LinkedIn professional networks, Facebook employment groups, university alumni associations, freelancing forums, career development communities, and WhatsApp groups. To ensure demographic diversity, stratification was applied based on gender, educational attainment, and urban-rural residence.

The target sample size ranged from 450 to 600 respondents. This sample size was considered sufficient for detecting medium effect sizes in multiple regression analyses involving interaction terms and moderation effects while maintaining adequate statistical power (80%) at a significance level of $\alpha = 0.05$.

Study Variables

The study examined several demographic and socio-economic characteristics as independent variables. These variables included age (18–24, 25–34, 35–44, and 45+ years), gender (male, female, non-binary/other), education level (secondary education or below, bachelor's degree, and master's degree or higher), socio-economic status based on household income quintiles, urban or rural residence, ethnicity, caste, or linguistic identity, digital literacy level, prior exposure to artificial intelligence technologies, and experience using online employment platforms.

The primary dependent variables included perceived algorithmic fairness, reported experiences of discrimination during AI-screened recruitment processes, trust in AI-based hiring systems, self-reported employment outcomes such as interview invitations and callback rates, and attitudes toward AI governance and regulation. An intersectionality index was constructed to evaluate the combined effects of gender, socio-economic status, and educational attainment on experiences of algorithmic bias.



Data Collection Instrument

Data were collected using a structured online questionnaire administered through Google Forms or Qualtrics. The questionnaire was developed based on validated instruments from previous studies examining algorithmic fairness, technology trust, digital discrimination, and AI governance. The survey consisted of five sections: demographic information, digital literacy assessment,

platform usage experience, perceptions of algorithmic fairness and discrimination, and attitudes toward AI regulation.

Perceived algorithmic fairness, trust in AI hiring systems, and attitudes toward AI governance were measured using multiple-item Likert scales ranging from 1 (strongly disagree) to 5 (strongly agree). Digital literacy was assessed through self-reported competencies and a brief objective knowledge quiz. Participants were also invited to provide qualitative comments regarding their experiences with AI-assisted hiring systems through optional open-ended questions.

Pilot Testing

Prior to the main survey, a pilot study involving approximately 30–50 participants were conducted to assess questionnaire clarity, reliability, and validity. Feedback from pilot respondents was used to refine survey items, improve wording, and ensure cultural appropriateness. Reliability analysis using Cronbach's alpha coefficient was performed to evaluate the internal consistency of multi-item scales. A Cronbach's alpha value of 0.70 or higher was considered acceptable.

Secondary Data Collection

To complement the primary survey findings, secondary data were collected from publicly available sources, including government reports, International Labour Organization publications, academic literature, platform transparency reports, and policy documents concerning AI-driven recruitment systems in South Asia. These materials provided contextual information regarding the adoption of AI hiring technologies, documented cases of algorithmic discrimination, and emerging regulatory frameworks.

Data Analysis

Data were analyzed using the Statistical Package for the Social Sciences (SPSS) version 29 and AMOS or SmartPLS for advanced modeling. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were calculated to summarize participant characteristics and key study variables.

Reliability analysis was performed using Cronbach's alpha to assess the internal consistency of the measurement scales. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were conducted to evaluate construct validity and verify the factor structure of the algorithmic fairness and trust measures.

Independent-samples t-tests and one-way Analysis of Variance (ANOVA) were used to examine differences in perceived algorithmic bias across demographic groups. Hierarchical multiple regression analysis was employed to investigate the influence of demographic, socio-economic, and technological factors on perceptions of fairness and trust in AI hiring systems. Logistic regression models were applied to examine predictors of reported discriminatory experiences and employment outcomes.

To assess intersectional effects, moderation analyses were conducted using the PROCESS macro in SPSS or Structural Equation Modeling (SEM). Interaction terms involving gender, socio-economic status, education level, and digital literacy were included to determine whether the impact of algorithmic bias differed across social groups. Statistical significance was determined at a p-value of less than 0.05.

Qualitative Analysis

Responses obtained from open-ended survey questions were analyzed using thematic analysis. Participant narratives were coded, categorized, and grouped into recurring themes related to experiences of discrimination, trust in AI systems, transparency concerns, and recommendations for fairer hiring practices. Qualitative findings were integrated with the quantitative results to provide a more comprehensive understanding of algorithmic bias and social inequality.

Ethical Considerations

Ethical approval was obtained from the relevant Institutional Review Board (IRB) prior to data collection. Participation was voluntary, and informed consent was obtained electronically from all respondents

before they accessed the survey. Participants were informed about the study objectives, confidentiality measures, and their right to withdraw at any stage without penalty. No personally identifiable information was collected, and all data were stored securely and analyzed in aggregate form to ensure participant anonymity and privacy.

RESULTS

A total of 550 respondents completed the online survey. Participants represented diverse demographic backgrounds across urban and rural areas of the Global South. The majority of respondents belonged to the 25–34 years age group (40.0%), followed by the 18–24 years category (32.7%). Female respondents constituted 47.3% of the sample, while males represented 49.1%.

Table 1: Demographic Profile of Participants (N = 550)

Variable	Category	Frequency (n)	Percentage (%)
Age	18–24	180	32.7
	25–34	220	40.0
	35–44	100	18.2
	45+	50	9.1
Gender	Male	270	49.1
	Female	260	47.3
	Non-binary/Other	20	3.6
Residence	Urban	360	65.5
	Rural	190	34.5
Education	Secondary or Less	90	16.4
	Bachelor's Degree	310	56.4
	Master's or Higher	150	27.3

The findings indicate that the sample included respondents from diverse educational and socio-economic backgrounds, providing adequate representation for further analyses.

Cronbach's alpha was used to assess the internal consistency of the survey scales.

Table 2. Reliability Statistics

Scale	Number of Items	Cronbach's α
Perceived Algorithmic Fairness	8	0.87
Trust in AI Hiring Systems	7	0.85
AI Governance Attitudes	6	0.82
Discrimination Experience Scale	5	0.80

All scales demonstrated acceptable reliability, with Cronbach's alpha values exceeding the recommended threshold of 0.70.

Descriptive statistics were calculated for the major study variables.

Table 3. Descriptive Statistics

Variable	Mean	SD	Minimum	Maximum
Perceived Algorithmic Fairness	2.94	0.81	1.00	5.00
Trust in AI Hiring Systems	2.76	0.89	1.00	5.00
Reported Discrimination Experiences	3.12	0.92	1.00	5.00
AI Governance Attitudes	4.08	0.69	1.00	5.00
Digital Literacy Score	7.41	1.88	2.00	10.00

Participants generally expressed moderate levels of trust and fairness perceptions toward AI hiring systems, while support for stronger AI governance was relatively high. An independent samples t-test was conducted to compare perceived algorithmic fairness scores between male and female respondents.

Table 4. Gender Differences in Perceived Algorithmic Fairness

Gender	Mean ± SD
Male	3.15 ± 0.76
Female	2.74 ± 0.81

Test	Value
t-value	5.84
p-value	<0.001

Female respondents reported significantly lower perceptions of fairness compared with male respondents ($p < 0.001$), suggesting greater concerns regarding algorithmic discrimination. A one-way ANOVA was performed to examine differences in trust levels across educational groups. Privacy and confidentiality were the most frequently reported ethical concerns among participants.

Table 5. Trust in AI Hiring Systems by Education Level

Education Level	Mean ± SD
Secondary or Less	2.45 ± 0.84
Bachelor's Degree	2.73 ± 0.87
Master's or Higher	3.02 ± 0.90

ANOVA Statistic	Value
F-value	8.62
p-value	<0.001

Respondents with higher educational attainment demonstrated significantly greater trust in AI hiring systems than those with lower educational qualifications. Pearson correlation analysis was conducted to examine relationships among the major study variables.

Table 6. Correlation Matrix

Variable	1	2	3	4
1. Algorithmic Fairness	1			
2. Trust in AI Systems	0.71**	1		
3. Discrimination Experiences	-0.62**	-0.58**	1	
4. AI Governance Attitudes	-0.34**	-0.29**	0.41**	1

** $p < 0.01$

Perceived fairness was positively associated with trust in AI systems and negatively associated with discrimination experiences. Participants who reported higher levels of discrimination were more supportive of AI governance and regulation. A hierarchical multiple regression analysis was conducted to identify predictors of perceived algorithmic fairness

Table 7. Multiple Regression Predicting Perceived Algorithmic Fairness

Predictor	β	t	p-value
Gender (Female)	-0.21	-5.74	<0.001
Education Level	0.17	4.32	<0.001
Digital Literacy	0.24	6.11	<0.001
AI Exposure Frequency	0.19	4.85	<0.001
Urban Residence	0.08	2.11	0.035

Model Statistics

Statistic	Value
R ²	0.42
Adjusted R ²	0.41
F-value	78.31
p-value	<0.001

The regression model explained 42% of the variance in perceived algorithmic fairness. Digital literacy emerged as the strongest positive predictor, while female gender was associated with lower fairness perceptions. Moderation analysis examined whether socio-economic status and education moderated the relationship between gender and perceived discrimination.

Table 8. Moderation Effects

Interaction Term	β	p-value
Gender × SES	-0.18	0.002
Gender × Education	-0.15	0.006
SES × Education	-0.11	0.021

Significant interaction effects indicate that women from lower socio-economic backgrounds and lower educational groups experienced the highest levels of perceived algorithmic discrimination. Participants were asked whether AI-assisted applications resulted in interview invitations or callbacks.

Table 9. Self-Reported Employment Outcomes

Outcome	Frequency	Percentage (%)
Received Callback	212	38.5
No Callback	338	61.5
Reported AI Rejection Concern	372	67.6
Believed AI Was Biased	321	58.4

More than half of respondents believed that AI-based recruitment systems may have negatively influenced their employment opportunities. Qualitative analysis identified four major themes:

Table 4.10. Major Themes from Open-Ended Responses

Theme	Representative Finding
Lack of Transparency	Participants reported uncertainty regarding how AI systems evaluate applications.
Perceived Discrimination	Respondents believed that gender, language, and educational background influenced outcomes.
Trust Deficit	Many participants expressed skepticism toward automated hiring decisions.
Demand for Regulation	Respondents favored stronger oversight and accountability mechanisms.

The qualitative findings reinforced the quantitative results by highlighting widespread concerns regarding fairness, transparency, and accountability in AI-driven recruitment systems. The results demonstrate significant concerns regarding algorithmic bias among job seekers in the Global South. Female respondents, individuals from lower socio-economic backgrounds, and those with lower educational attainment reported greater experiences of discrimination. Digital literacy and prior exposure to AI technologies were positively associated with trust and fairness perceptions. Furthermore, strong support emerged for enhanced AI governance and regulatory oversight of automated hiring systems.

DISCUSSION

The present study examined perceptions of algorithmic bias in AI-driven hiring platforms and its intersectional impact on social inequality among job seekers in the Global South. The findings revealed that respondents reported moderate levels of trust in AI hiring systems, relatively low perceptions of algorithmic fairness, and substantial concerns regarding discrimination during AI-assisted recruitment processes. These findings support growing international concerns that automated hiring technologies may reproduce and amplify existing social inequalities rather than eliminate them (Ferrara, 2023; Kordzadeh & Ghasemaghaei, 2022; Tilmes, 2022).

A key finding of this study was that female respondents reported significantly lower perceptions of algorithmic fairness than male respondents and were more likely to perceive discriminatory outcomes during recruitment. This finding is consistent with previous research demonstrating that AI hiring systems can inherit gender biases from historical employment data and organizational practices (Vivek, 2023). AI recruitment tools frequently reproduce gender inequalities because machine-learning systems are often trained on biased historical hiring decisions, resulting in discriminatory outcomes against women and other marginalized groups (Chang, 2023). Similarly, algorithmic hiring systems operate within broader social structures where existing inequalities are encoded into recruitment datasets, thereby perpetuating discriminatory patterns rather than removing them (Franklin et al., 2024; Zajko, 2021).

The results further demonstrated that respondents with lower educational attainment and lower socio-economic status reported greater experiences of algorithmic discrimination. This finding supports the concept of digital inequality, which suggests that technological systems disproportionately disadvantage already marginalized populations (Tilmes, 2022). Previous studies have shown that individuals with fewer educational resources often have limited access to digital skills, making them more vulnerable to exclusion in technology-mediated environments (Kshetri, 2021; Kukulska-Hulme et al., 2023). The observed disparities may reflect the inability of automated hiring systems to adequately recognize diverse educational backgrounds, informal qualifications, and non-traditional career pathways commonly found among job seekers in developing countries (Kassir et al., 2023; Kshetri, 2021; Yarger et al., 2020). These findings align with research emphasizing that algorithmic decision-making can reinforce structural inequalities by privileging applicants whose profiles closely resemble historically successful candidates (Ferrara, 2023; Ntoutsis et al., 2020).

One of the most important findings of this study was the significant role of digital literacy in shaping perceptions of fairness and trust. Respondents with higher digital literacy scores reported greater trust in AI hiring systems and perceived recruitment algorithms as more transparent and fair. This finding is supported by technology acceptance research, which suggests that individuals who better understand technological systems are more likely to perceive them as trustworthy and beneficial. Digital literacy may enhance individuals' ability to interpret automated decisions, optimize online profiles, and effectively navigate digital recruitment platforms. Consequently, digital literacy appears to function as a protective factor against perceptions of exclusion and uncertainty within AI-mediated labor markets (Kshetri, 2021).

The correlation analysis demonstrated a strong positive relationship between perceived algorithmic fairness and trust in AI hiring systems. Conversely, respondents who reported experiences of discrimination exhibited lower trust levels and stronger support for government regulation. These findings are consistent with studies indicating that transparency and explainability are critical determinants of public trust in artificial intelligence (Ochmann et al., 2024). When individuals perceive recruitment algorithms as opaque or biased, confidence in technological decision-making decreases substantially. Previous scholarship has emphasized that algorithmic transparency, accountability mechanisms, and explainable AI frameworks are essential for maintaining public trust and reducing concerns

regarding automated discrimination (Ferrara, 2023).

The moderation analysis revealed significant intersectional effects involving gender, socio-economic status, and education. Women belonging to lower socio-economic groups and possessing lower educational qualifications reported the highest levels of perceived discrimination. This finding strongly supports intersectionality theory, which argues that social disadvantages do not operate independently but instead interact to create compounded forms of inequality (Bambra, 2022; Wang et al., 2022). Rather than experiencing discrimination solely because of gender or socio-economic status, individuals occupying multiple marginalized identities may face unique barriers that cannot be explained by any single demographic characteristic alone. Similar conclusions have been reported in contemporary algorithmic fairness research, which emphasizes that automated hiring systems often disproportionately affect individuals located at the intersection of multiple vulnerable social categories (Wang et al., 2022; Yarger et al., 2020).

The employment outcome analysis indicated that more than half of respondents believed AI-driven recruitment systems negatively influenced their chances of obtaining interviews and employment opportunities. Furthermore, only a minority reported receiving callbacks after submitting applications through automated platforms. Although self-reported outcomes cannot establish causal relationships, these perceptions are important because they influence applicant behavior, trust, and willingness to participate in digital labor markets. Recent research on AI recruitment has similarly documented concerns regarding unequal employment outcomes and the potential for algorithmic systems to influence access to employment opportunities (Kassir et al., 2023). Research examining job recommender systems found that algorithmic recommendations can vary according to gender and demographic characteristics, thereby influencing employment trajectories and labor market opportunities (Franklin et al., 2024).

The thematic analysis provided further support for the quantitative findings. Participants repeatedly highlighted concerns regarding lack of transparency, perceived discrimination, trust deficits, and the need for stronger regulation. These themes closely mirror international debates concerning ethical AI governance (Ferrara, 2023). Transparency remains one of the most persistent challenges associated with automated hiring because applicants often receive little information regarding how algorithms evaluate resumes, rank candidates, or determine suitability for employment (Ochmann et al., 2024). As a result, individuals may perceive recruitment outcomes as arbitrary and unfair, even when organizations claim that AI systems improve efficiency and objectivity. Similar concerns have been documented across numerous studies investigating the ethical implications of automated hiring technologies (Kassir et al., 2023; Kordzadeh & Ghasemaghaei, 2022).

The findings of this study have important implications for policymakers, employers, and technology developers. First, organizations deploying AI hiring systems should conduct regular bias audits to identify and mitigate discriminatory outcomes (Ferrara, 2023). Second, algorithmic transparency should be enhanced by providing applicants with meaningful explanations regarding automated decisions. Third, governments in the Global South should establish regulatory frameworks that ensure accountability, fairness, and compliance with anti-discrimination principles. Finally, initiatives aimed at improving digital literacy among disadvantaged populations may help reduce inequalities in access to AI-mediated employment opportunities (Kshetri, 2021).

Despite its contributions, this study has several limitations. The use of online convenience and snowball sampling may limit the generalizability of findings to all job seekers in the Global South. Additionally, employment outcomes and discrimination experiences were self-reported and may be influenced by recall bias or subjective interpretation. Future studies should combine survey methods with experimental audits of recruitment platforms and longitudinal

analyses of actual hiring outcomes. Comparative research across multiple countries would also provide a deeper understanding of how cultural, economic, and regulatory contexts shape experiences of algorithmic bias.

Overall, the findings suggest that AI-driven hiring platforms may inadvertently reproduce existing social inequalities, particularly among women, individuals with lower socio-economic status, and those with limited educational opportunities. The significant interaction effects observed in this study demonstrate that algorithmic fairness cannot be evaluated through single demographic categories alone. Instead, policymakers and technology developers must adopt intersectional approaches that recognize the complex ways in which multiple social identities influence experiences within AI-mediated recruitment systems (Wang et al., 2022). Ensuring fairness, transparency, and accountability in automated hiring will therefore be essential for promoting equitable employment opportunities and inclusive digital labor markets in the Global South (Kshetri, 2021).

CONCLUSION

This study investigated algorithmic bias in AI-driven hiring platforms and its intersectional impact on social inequality among job seekers in the Global South. findings reveal that trust in automated recruitment and perceptions of discrimination vary significantly across demographic lines, with women and lower-income respondents reporting greater disadvantage. compounding vulnerabilities highlight urgent transparency and accountability needs in AI deployment. policymakers, employers, and developers must adopt inclusive, ethical practices to ensure equitable employment access. future research should pursue longitudinal and cross-country perspectives to further evaluate societal implications.

Ethical Considerations

The study adhered to relevant ethical principles. Informed consent was obtained from all participants prior to participation. Participation was voluntary, and confidentiality and anonymity were maintained throughout the study.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Author Contributions

Abubakar Tayyab: Study design, data collection, statistical analysis, and drafting and writing of the manuscript.

Syed Muhammad Ayub Shah: Study design, data interpretation, critical revision of the manuscript, and final approval of the version to be published.

Funding

No external funding was received for this study.

Conflict of Interest

The author declares no conflict of interest.

Acknowledgments

The authors sincerely acknowledge the participation of the job seekers and platform users who contributed to this study, as well as the individuals and organizations that assisted with participant recruitment and data collection.

Use of Artificial Intelligence

ChatGPT was used for language and grammar collection. Gemini AI was used for figure generation.

REFERENCES

- Albassam, W. A. (2023). The power of artificial intelligence in recruitment: An analytical review of current AI-based recruitment strategies. *International Journal of Professional Business Review*, 8(6), 4. <https://doi.org/10.26668/businessreview/2023.v8i6.2089>
- Ali, I., Mughal, N., Khand, Z. H., Ahmed, J., & Mujtaba, G. (2022). Resume classification system using natural language processing and machine learning techniques. *Mehran University Research Journal of Engineering and Technology*, 41(1), 65–79. <https://doi.org/10.22581/muet1982.2201.07>
- Arora, A., Barrett, M., Lee, E., Oborn, E., & Prince, K. (2023). Risk and the future of AI: Algorithmic bias, data colonialism, and marginalization. *Information and Organization*, 33(3), 100478. <https://doi.org/10.1016/j.infoandorg.2023.100478>
- Bambra, C. (2022). Placing intersectional inequalities in health. *Health & Place*, 75, 102761. <https://doi.org/10.1016/j.healthplace.2022.102761>
- Chaka, C. (2022). Digital marginalization, data marginalization, and algorithmic exclusions: A critical southern decolonial approach to datafication, algorithms, and digital citizenship from the Souths. *International Journal of E-Learning & Knowledge Society*, 18(3), 83–95. <https://doi.org/10.20368/1971-8829/1135678>
- Chang, X. (2023). Gender bias in hiring: An analysis of the impact of Amazon's recruiting algorithm. *Advances in Economics, Management and Political Sciences*, 23(1), 134–140. <https://doi.org/10.54254/2754-1169/23/20230367>
- Ferrara, E. (2023). Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. *Sci*, 6(1), 3. <https://doi.org/10.3390/sci6010003>
- Franklin, G., Stephens, R., Piracha, M., Tiosano, S., Lehouillier, F., Koppel, R., et al. (2024). The sociodemographic biases in machine learning algorithms: A biomedical informatics perspective. *Life*, 14(6), 652. <https://doi.org/10.3390/life14060652>
- Kartal, E. (2022). A comprehensive study on bias in artificial intelligence systems: Biased or unbiased AI, that's the question! *International Journal of Intelligent Information Technologies*, 18(1), 1–23. <https://doi.org/10.4018/IJIT.309582>
- Kassir, S., Baker, L., Dolphin, J., & Polli, F. (2023). AI for hiring in context: A perspective on overcoming the unique challenges of employment research to mitigate disparate impact. *AI and Ethics*, 3(3), 845–868. <https://doi.org/10.1007/s43681-022-00208-x>
- Kordzadeh, N., & Ghasemaghaei, M. (2022). Algorithmic bias: Review, synthesis, and future research directions. *European Journal of Information Systems*, 31(3), 388–409. <https://doi.org/10.1080/0960085X.2021.1927212>
- Kshetri, N. (2021). Evolving uses of artificial intelligence in human resource management in emerging economies in the Global South: Some preliminary evidence. *Management Research Review*, 44(7), 970–990. <https://doi.org/10.1108/MRR-03-2020-0168>
- Kukulska-Hulme, A., Giri, R. A., Dawadi, S., Devkota, K. R., & Gaved, M. (2023). Languages and technologies in education at school and outside of school: Perspectives from young people in low-resource countries in Africa and Asia. *Frontiers in Communication*, 8, 1081155. <https://doi.org/10.3389/fcomm.2023.1081155>
- Mariani, K., & Vega-Lozada, F. (2023). The use of AI and algorithms for decision-making in workplace recruitment practices. *Journal of Student Research*, 12(1).
- Mhlanga, D. (2022). Human-centered artificial intelligence: The superlative approach to achieve sustainable development goals in the fourth industrial revolution. *Sustainability*, 14(13), 7804. <https://doi.org/10.3390/su14137804>
- Ntoutsis, E., Fafalios, P., Gadiraju, U., Iosifidis, V., Nejdli, W., Vidal, M.-E., et al. (2020). Bias in data-driven artificial intelligence systems—An introductory survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 10(3), e1356. <https://doi.org/10.1002/widm.1356>
- Ochmann, J., Michels, L., Tiefenbeck, V., Maier, C., & Laumer, S. (2024). Perceived algorithmic fairness: An empirical study of transparency and anthropomorphism in algorithmic recruiting. *Information Systems Journal*, 34(2), 384–414. <https://doi.org/10.1111/isj.12482>
- Păvăloaia, V. D., & Necula, S. C. (2023). Artificial intelligence as a disruptive technology—A systematic literature review. *Electronics*, 12(5), 1102. <https://doi.org/10.3390/electronics12051102>
- Sambasivan, N., Arnesen, E., Hutchinson, B., Doshi, T., & Prabhakaran, V. (2021). Re-imagining algorithmic fairness in India and beyond. In

Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (pp. 315–328). Association for Computing Machinery. <https://doi.org/10.1145/3442188.3445896>

Tian, X., Pavur, R., Han, H., & Zhang, L. (2023). A machine learning-based human resources recruitment system for business process management: Using LSA, BERT and SVM. *Business Process Management Journal*, 29(1), 202–222. <https://doi.org/10.1108/BPMJ-08-2022-0389>

Tilmes, N. (2022). Disability, fairness, and algorithmic bias in AI recruitment. *Ethics and Information Technology*, 24(2), 21. <https://doi.org/10.1007/s10676-022-09633-2>

Vivek, R. (2023). Enhancing diversity and reducing bias in recruitment through AI: A review of strategies and challenges. *Informatics Economics Management*, 2(4), 0101–0118.

Wang, A., Ramaswamy, V. V., & Russakovsky, O. (2022). Towards intersectionality in machine learning: Including more identities, handling underrepresentation, and performing evaluation. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (pp. 336–349). Association for Computing Machinery. <https://doi.org/10.1145/3531146.3533101>

Yarger, L., Cobb Payton, F., & Neupane, B. (2020). Algorithmic equity in the hiring of underrepresented IT job candidates. *Online Information Review*, 44(2), 383–395. <https://doi.org/10.1108/OIR-10-2018-0334>

Zajko, M. (2021). Conservative AI and social inequality: Conceptualizing alternatives to bias through social theory. *AI & Society*, 36(3), 1047–1056. <https://doi.org/10.1007/s00146-021-01153-9>