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MITIGATING ALGORITHMIC BIAS IN AI-DRIVEN HIRING SYSTEMS IN THE UNITED STATES

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Abstract

The purpose of the research is to familiarise itself with the problems that shape the mitigation of algorithm bias in hiring systems founded on AI in the United States. Particularly, it investigates the contribution of awareness, bias belief, mitigation, organisational practices and implementation issues to the judgement of the trust and fairness of the AI-based recruitment process. The study presents the quantitative method of research and conducts a survey interviewing 300 HR professionals, recruiters, data scientists and managers. This questionnaire included 26 questions and a five-point Likert-type scale. Data analysis was conducted with the help of descriptive analysis, reliability tests, correlation, regression, and ANOVA to compare and investigate associations between variables.

The results indicate that awareness and perception of algorithm bias are high in the sample. The strongest predictor of trust and results was mitigation strategies followed by practices. Correlation analysis revealed that there was positive relationship between awareness, mitigation strategies and trust and negative relationship between challenges and all the key variables. The regression analysis demonstrated that the 61% of the variance in outcomes and trust was explained by the framework.

The study will provide effective recommendations to companies interested in implementing ethical AI-based recruitment technologies. It points to the necessity to introduce effective methods of bias reduction, enhance governance, and train employees. It further emphasizes the need to overcome implementation obstacles, including technical limitations and resource distributions, to promote fairness and transparency. This study adds to the AI ethics research literature by providing empirical evidence on bias minimization in employment algorithms. It combines both technical and organisational and perceptual variables into a single framework and offers insights into the manner through which trust and fairness can be achieved in AI-powered hiring systems.

Keywords

Algorithmic Bias, Artificial Intelligence, AI-driven Hiring, Recruitment Systems, Bias Mitigation, Organizational Practices, Trust, Ethical AI

1. Introduction

The fast development of artificial intelligence (AI) has transformed business processes, particularly the sphere of human resource management and recruitment. In the US many companies are currently employing AI-based hiring systems to automate and speed up the hiring process, enhance efficiency, and aid decision-making (Albaroudi et al., 2024). These technologies make use of algorithms, machine learning, and data mining to filter resumes, shortlist and even first interviews (Wallace, 2025). These technologies have been integrated with great benefits, but it also raised the issue of equity, transparency, and ethical issues, especially with regard to algorithmic bias.

Algorithms bias is also systematic and unjust discrimination in AI systems, which may be caused by biased training data, improper model design, or reproduction of historical injustices using data. This may cause some groups to be excluded or under-represented in the recruitment process and affect diversity and equal opportunity at work (Agarwal et al., 2025). Although it is often assumed that AI systems are free of bias, studies show that they have the potential to reproduce and even enhance the biases of the past unless they are created and managed appropriately.

There is growing awareness of the need to combat algorithmic bias to promote the ethical use of AI in organisations. The strategies to mitigate bias can include diverse data sources, open algorithms, regular audits, and human control (Mujtaba and Mahapatra, 2024). However, the implementation and effectiveness of these strategies in the organizational practice are under the scrutiny. Also, organizational activities, including policies, training, and governance, have a significant effect on the results of AI-based recruitment (Mohiuddin & Farhan, 2025; Cruz, 2024).

There is also a rise in the use of AI technology in hiring, which has an impact on the attitude of the stakeholders, particularly trust and acceptance. Job candidates and HR specialists might feel that the quality and fairness of AI systems are undermined, especially when the decision-making procedure is not transparent (Sony et al., 2025). Acceptance and adoption of AI hiring systems also rest on the premise of trust, which, in turn, depends on the perceived fairness and effectiveness of bias reduction measures. In addition, limiting the mitigation of algorithmic bias can also be constrained by the high cost, absence of technical expertise, and insufficient regulation (Amin et al., 2024).

The study seeks to understand the key factors that influence the reduction of algorithmic bias in AI-based recruitment systems in the United States. It studies the impact of variables like awareness, perceived bias, mitigation efforts, organisational practices, and challenges on the results such as trust and fairness. The study aims to provide a comprehensive perspective of how organisations would counteract the effect of algorithmic bias and enjoy the benefits of AI in recruitment by analysing these factors.

This research has value in that; it may help to solve the overlap between technology and ethics. With the adoption of AI as a new technology in the recruitment process, it is important to make sure the technology is fair and transparent to every individual. Our study contributes to the field of research on AI ethics and offers an indication of which practices should be implemented by organisations that decide to engage in responsible hiring practices using AI.

1.1 Problem Statement

Despite the growing adoption of AI hiring systems in the U.S., algorithmic bias is a source of concern among most organisations. These solutions, despite being aimed at enhancing efficiency and objectivity are usually founded on historic data that may be prejudiced in terms of gender, racial or socioeconomic factors. Therefore, AI technology can unintentionally support biased employment, as it can choke diversity and equal opportunity.

Although a number of measures to minimize bias are suggested, such as algorithmic audits, explainable models and human supervision, their implementation in organisations is still imbalanced and inefficient. In addition, most organisations lack strong policies, technical expertise and ethical training to deal with such issues. This leads to a disconnect between AI-driven hiring processes and its ethical application in practice.

Moreover, algorithmic bias undermines trust between various stakeholders, such as applicants and human resources managers. Lack of trust and transparency could challenge implementation of AI in hiring. Thus, the need to explore factors affecting bias mitigation in algorithms and what could be done to promote fairness, transparency, and trust in AI-based hiring systems is even more pressing.

1.2 Research Questions

1. What is the level of awareness regarding AI-driven hiring systems among professionals?

2. How do individuals perceive algorithmic bias in AI-based recruitment?
3. What mitigation strategies are most effective in reducing algorithmic bias?
4. How do organizational practices influence the fairness of AI-driven hiring systems?
5. What is the relationship between mitigation strategies and trust in AI systems?
6. How do challenges affect the implementation of bias mitigation strategies?

1.3 Research Objectives

1. To examine the level of awareness of AI in hiring systems.
2. To analyze perceptions of algorithmic bias in recruitment processes.
3. To evaluate the effectiveness of bias mitigation strategies.
4. To assess the role of organizational practices in reducing bias.
5. To determine the impact of mitigation strategies on trust and outcomes.
6. To identify key challenges in implementing fair AI systems.

2. Literature Review

2.1 AI in Recruitment and Hiring Systems of US

Artificial intelligence has been applied in hiring and this has revolutionized the recruitment process by eliminating some of the most tedious duties involved in the process such as sifting through resumes, pairing companies with candidates and scheduling interviews. AI-driven Hiring systems are supposed to facilitate the workflow and reduce human interaction to enable the rapid and effective screening of the mass of applicants (Twaha, 2024). These tools apply machine learning concepts to data and estimate the fit of the candidate according to predetermined parameters. Despite the increase in efficiency, the use of AI has been criticized because of the question of fairness and transparency (Amin, 2025).

2.2 Concept of Algorithmic Bias in US markets

The source of algorithmic bias is when the AI systems produce biased results toward a particular group. Prejudice has its roots in past statistics that support the existing disparities in society (Samala and Rawas, 2024). Indicatively, during the hiring process, biased algorithms can discriminate against a given group, and thus make it unrepresented in the workforce. Instead, it may be difficult to identify and correct biases because many AI systems are black-box, and it may be hard to detect potential issues (Imtiaz et al., 2025). To fight against algorithmic bias, one should know how it works and what consequences it has.

2.3 Mitigation Strategies for Bias Reduction in US markets

There are a number of ways to combat algorithmic bias in AI recruitment. As an example, the necessity to make sure that there is various training data to create AI models to prevent disproportionate bias in favor of some groups (Imtiaz et al., 2024). It is also important that the process of algorithmic auditing is continuous to identify and reduce biases. Improving the transparency of AI, including explainable algorithms, enhances accountability because it allows users to learn how decisions are formed (Choain et al., 2023; Mohiuddin, 2024). And humans in the loop implies that AI decisions are reviewed and confirmed, which reduces the possibility of biased outcomes.

2.4 Organizational Practices and Ethical AI of US

The effectiveness of AI systems is also based on organisational practices. Implementation of AI technologies can be made responsible by having policies and ethical frameworks in place (Harris, 2024). Ethical AI training can enhance the level of awareness about biases among employees and give them tools to reduce such impacts (Hasan et al., 2025). Moreover, organizations, which place a premium on diversity and equity, tend to have an effective bias reduction policy. Good governance systems are also necessary in order to uphold accountability and adherence to ethical practices.

2.5 Trust and Outcomes in AI-Driven Hiring of US

One of the major motives behind using AI systems to hire is trust. The more the stakeholders believe the AI technologies are just, transparent and reliable, the more likely they will embrace and incorporate them (Alim et al., 2025). Attempts to prevent bias contribute to building trust since they will show an interest in

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being fair. The advantages of AI technologies such as a greater degree of diversity and performance contribute to trust as well. However, when there is bias, we lose these benefits and we end up mistrusting one another.

2.6 Challenges in Mitigating Algorithmic Bias of US

Despite the possibility of dealing with bias, eliminating algorithmic bias in organizations has obstacles (Ahmad, 2024). Insufficient technical knowledge and skills may hinder the development of fair algorithms. The relative expense of advanced technologies and auditing can also be out of bounds, particularly to smaller companies (Islam, 2023). Furthermore, uncertainty and lack of regulatory clarity restrict responsibility and certainty (Ahmed et al., 2022). It is also worthwhile that policymakers, organizations and technology providers collaborate to overcome these challenges.

2.7 Significance of the Research

The current study comes as a very topical one in the context of the widespread application of artificial intelligence (AI) in recruitment. As the trend of recruitment with the help of AI-based systems is on the rise, it is becoming imperative to ensure that the decision making is equitable, transparent and high quality. This research contributes to the knowledge of how to reduce the biases of algorithms through the awareness interventions and organisational practices.

This study has given significant feedback to HR practitioners, policy makers and technologists by identifying the factors that affect trust and equity in AI-based recruitment. It highlights the importance of strong bias mitigation and strengthening control practices, such as audits, open-source algorithms and ethics, to enhance the reliability of AI systems. It further emphasizes the role of organisational practices and training as a way to guarantee ethical AI use.

Additionally, this research contributes to the existing literature by offering empirical evidence on the relationship between bias mitigation and recruitment. It also offers a foundation to the future studies of ethical AI practices. Lastly, the research will help to develop balanced and equal employment procedures that can offer all applicants an opportunity and make the potential of AI effective.

3. Methodology

3.1 Research Design

Through a quantitative method, this study examines the issues that influence the mitigation of algorithmic bias in AI-based hiring techniques in the United States. The surveys were conducted using a cross-sectional survey design with the sample of recruitment, human resources, and AI-related jobs. Quantitative design was chosen as it will be possible to measure the relations between the variables including awareness, perception of bias, mitigation measures, company practices, challenges, and trust. Further, the method enables statistical analysis ensuring the results are generalisable and objective.

3.2 Population and Sampling

Individuals with industries often using AI hiring systems like IT, finance, health care and education were taken as the population of the study. This group formed an HR practitioner, recruiters, data scientists and managers with various levels of experience.

Convenience sampling was used to select a sample of 300 respondents since it is easy to access and the sample is relevant. The sample size was considered to be adequate statistically and was a heterogeneous sample in terms of gender, age, education and work experience, which enhanced the reliability and generalizability of the study findings.

3.3 Data Collection Instrument

Data was collected using a structured questionnaire consisting of 26 items designed to measure the key constructs of the study. The questionnaire was divided into two main sections:

- **Demographic Information:** Includes variables such as gender, age, educational qualification, job role, experience, and industry sector.
- **Main Constructs:** Measures six key variables:
    - Awareness of AI
    - Algorithmic Bias Perception

- Mitigation Strategies
- Organizational Practices
- Challenges
- Outcomes & Trust

All items were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), allowing respondents to express their level of agreement with each statement.

3.4 Data Collection Procedure

The survey instrument was presented digitally through online platforms to the sample and made it easy to use and reach an audience of more people. The respondents were informed of the study and assured confidentiality and anonymity. The questionnaire was self-administered, and the respondents were requested to respond to the questions according to their experience with AI-driven hiring systems.

3.5 Reliability and Validity

Internal consistency was checked by testing the measuring instrument with Cronbachs Alpha. The results indicated high reliability of all constructs with a range of 0.81 to 0.91 and overall reliability of 0.93 which is greater than the recommended reliability of 0.70.

The content validity was met through well-considered questionnaire items that were created through literature reviews and other theories. All aspects of mitigation of algorithmic bias and determinants were addressed in the questionnaire.

3.6 Data Analysis Techniques

The collected data was analyzed using statistical software to generate meaningful insights. The following techniques were employed:

- **Descriptive Statistics:** To summarize demographic characteristics and calculate mean and standard deviation for all constructs.
- **Reliability Analysis:** To assess internal consistency using Cronbach's Alpha.
- **Correlation Analysis:** To examine relationships among variables.
- **Regression Analysis:** To determine the impact of independent variables (awareness, bias perception, mitigation strategies, organizational practices, and challenges) on the dependent variable (outcomes & trust).
- **ANOVA:** To identify significant differences among groups.

These statistical methods provided a comprehensive understanding of the relationships and effects among the study variables.

3.7 Ethical Considerations

There was adherence to ethical standards in the course of the research. An overview of the study was given to the respondents, and they were asked to give consent to the study prior to the data collection. Anonymity and privacy were also ensured and no identifying data was included. Data were utilized exclusively as research data, and ethical standards and transparency in research were maintained.

4. Findings of the Study/Results

Findings of the study- Findings of the study refers to the part, in which the researcher states the findings of the research in a non-subjective and objective manner. It provides the key findings of the data analysis in terms of patterns, correlations and trends that were found in the study. In this section, I can only report the data without any interpretation or explanation as it is done in the discussion section.

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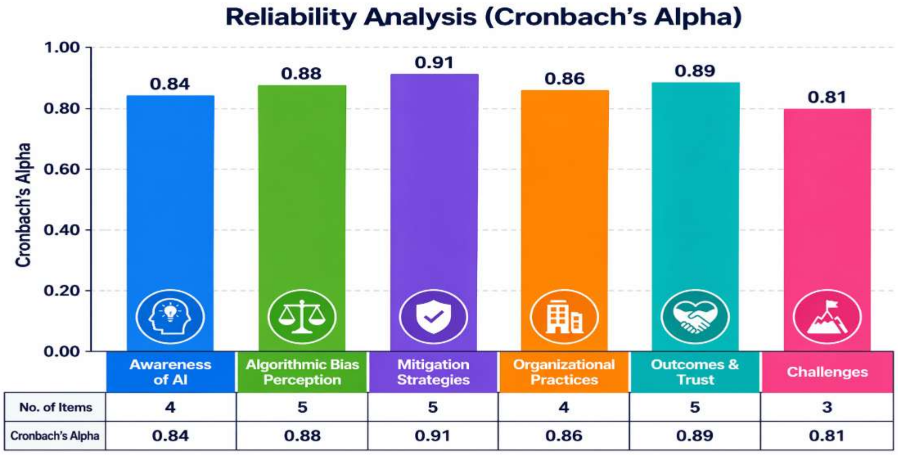
Figure 1
Reliability Analysis



The constructs are highly internally consistent as per our findings. The scores of Cronbach Alpha lie between 0.81 and 0.91, much higher than acceptable 0.70. The reliability of the construct of Mitigation Strategies is the highest (0.91), which indicates that items in the construct are very consistent. Similarly, such constructs as "Outcomes & Trust" (alpha = 0.89) and "Algorithmic Bias Perception" (alpha = 0.88) are also highly reliable, meaning that they will reliably measure these constructs. The internal consistency of the items in the constructs of the two variables is good (Organizational Practices 0.86 and Awareness of AI 0.84) with the value of "Challenges" being low, yet acceptable (0.81).

The scale has a very high reliability (α = 0.93) indicating that the 26 items are highly reliable and consistent in measuring the latent constructs. These findings suggest that the measurement model is sound and can be subjected to further statistical tests.

Table 1
Demographic Information

Variable	Category	Frequency	Percentage
Gender	Male	178	59.3%
	Female	122	40.7%
Age Group	18–25	68	22.7%
	26–35	126	42.0%
	36–45	62	20.7%
	46–55	30	10.0%
	56+	14	4.6%
Educational Qualification	Bachelor’s	132	44.0%
	Master’s	118	39.3%
	PhD	50	16.7%
Current Role	HR Professional	85	28.3%
	Recruiter	72	24.0%
	Data Scientist	48	16.0%
	Manager	60	20.0%
	Other	35	11.7%
Years of Experience	Less than 1 year	40	13.3%
	1–3 years	82	27.3%
	4–7 years	96	32.0%

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Variable	Category	Frequency	Percentage
	8–12 years	52	17.3%
	13+ years	30	10.0%
Industry Sector	IT	102	34.0%
	Finance	58	19.3%
	Healthcare	46	15.3%
	Education	54	18.0%
	Other	40	13.4%

The sample is average in both genders having 59.3% men and 40.7% women. Even though it is a skewed distribution towards males, the sample is diverse.

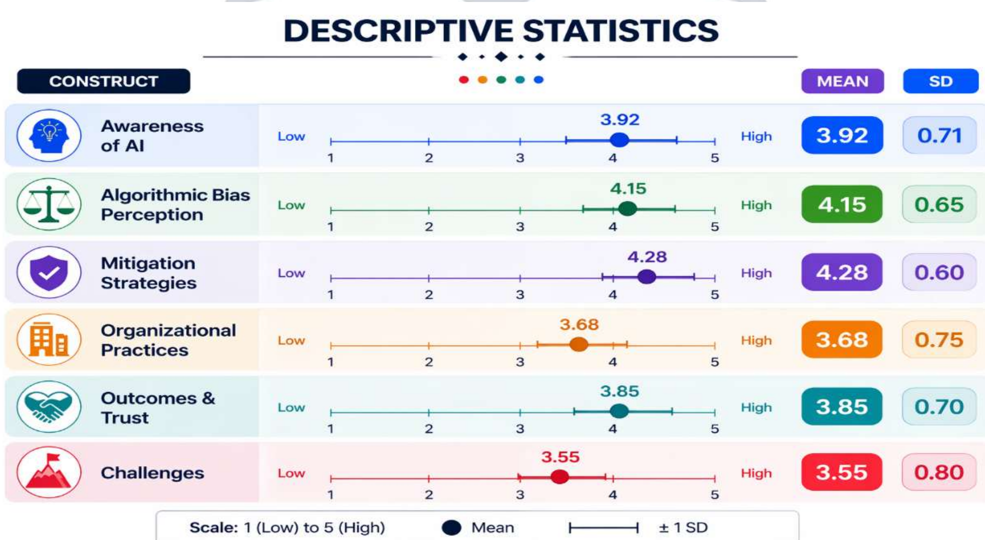
In terms of age, the majority of respondents fall within the 26–35 age group (42.0%), followed by 18–25 (22.7%) and 36–45 (20.7%). This shows that the sample is mostly represented by early to mid-career professionals, with little representation of older age groups (46+ collectively 14.6%).

The sample is highly-educated: 83.3% have at least a bachelors degree. The most common is the respondents that have a bachelors degree (44.0%), then there are those with a masters (39.3%), and the least common are those with PhDs (16.7%). It means the sample will be very educated and thus they will be able to grasp complex ideas such as AI and prejudice.

HR (28.3%) and recruiters (24.0%) are the two highest in terms of current employment with over 50 percent of the sample. Other important roles are played by managers (20.0%) and data scientists (16.0), who offer a managerial and technology viewpoint respectively. The level of experience among the participants is high, with a higher proportion of mid-career professionals: 4-7 years (32.0%), and 1-3 years (27.3%). We have 27.3% experienced professionals (8+ years) and 13.3% new professionals (<1 year). This is a good representation with a little skew towards the middle-career professionals.

Finally, the industry breakdown depicts an IT (34.0%) preponderant, then the finance (19.3%), education (18.0%) and healthcare (15.3%) with 13.4% other industry. The saliency of IT implies that it will be very applicable to AI-related concerns and the combination of industries contributes to the overall applicability of research findings. Overall, the sample is both diverse in demographics and well-educated and applicable to the research, and the percentage of individuals who will be willing to utilize AI in their work is high.

Figure 2
Descriptive Statistics



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Descriptive statistics indicate that the mean scores of all constructs are quite high, which is indicative of a positive attitude towards AI-related concepts. The largest mean value (M = 4.28, SD = 0.60) is observed in the group of Mitigation Strategies, which indicates that the strategies to reduce AI-related issues are highly agreed upon and widely acceptable. The second-largest mean (M = 4.15, SD = 0.65) represents the case of Perception of Algorithmic Bias according to which the respondents are very conscious about the problem of algorithmic bias.

The means on Awareness of AI (M = 3.92, SD = 0.71) and Outcomes and Trust (M = 3.85, SD = 0.70) are also high, which implies that the participants are aware of AI and have substantial trust in the outcomes. The mean on Outcomes and Trust is a little lower, which could mean some doubt despite awareness.

The lower means of the Organizational Practices (M = 3.68, SD = 0.75) and of Challenges (M = 3.55, SD = 0.80) mean that there could be a weakness in organisational practices and in the ability to successfully apply AI systems. The higher standard deviation of Challenges suggests that the respondents differ in their perceptions, and this suggests that there can be a difference in the challenges associated with AI.

Overall, the findings suggest the high awareness and active use of AI and working on bias, however, comparatively lower support levels and obstacles to its implementation and use.

Figure 3

Correlation matrix

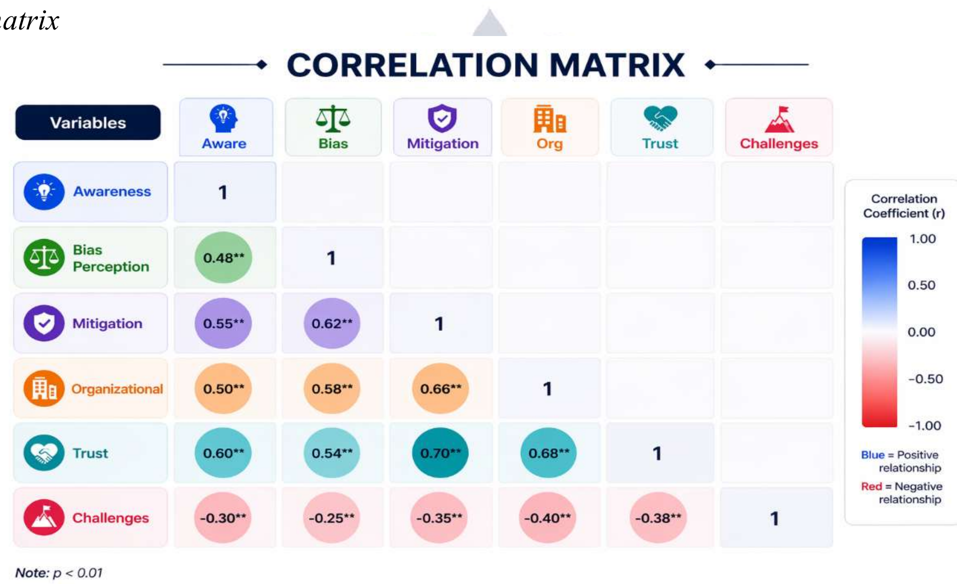

Table of correlations where all is well, and the negatives are also timely. The statistical harmony is normally suspect, but you know, you have it, so go on.

The findings show that there are significant correlations between all the variables ($p < 0.01$), meaning that there are relationships in the model. AI Awareness is positively correlated to Bias Perception ($r = 0.48$), Mitigation Strategies ($r = 0.55$), Organizational Practices ($r = 0.50$) and Trust ($r = 0.60$). This means that the more aware individuals are, the more aware they are of bias, the better the mitigation strategies, the better the organisational practices and the trust into AI systems.

Mitigation Strategies ($r = 0.62$), Organizational Practices ($r = 0.58$), and Trust ($r = 0.54$) are also positively related with Perception of Algorithmic Bias. This suggests that people who perceive themselves as biased, take mitigation strategies and organisational practices which are positively associated with trust.

Mitigation Strategies have also positive correlations with Organization practices ($r = 0.66$) and Trust ($r = 0.70$), which are some of the highest correlations in the model. This implies that the effective mitigation strategies are inherently connected to the institutional support and are associated with the trust in AI systems.

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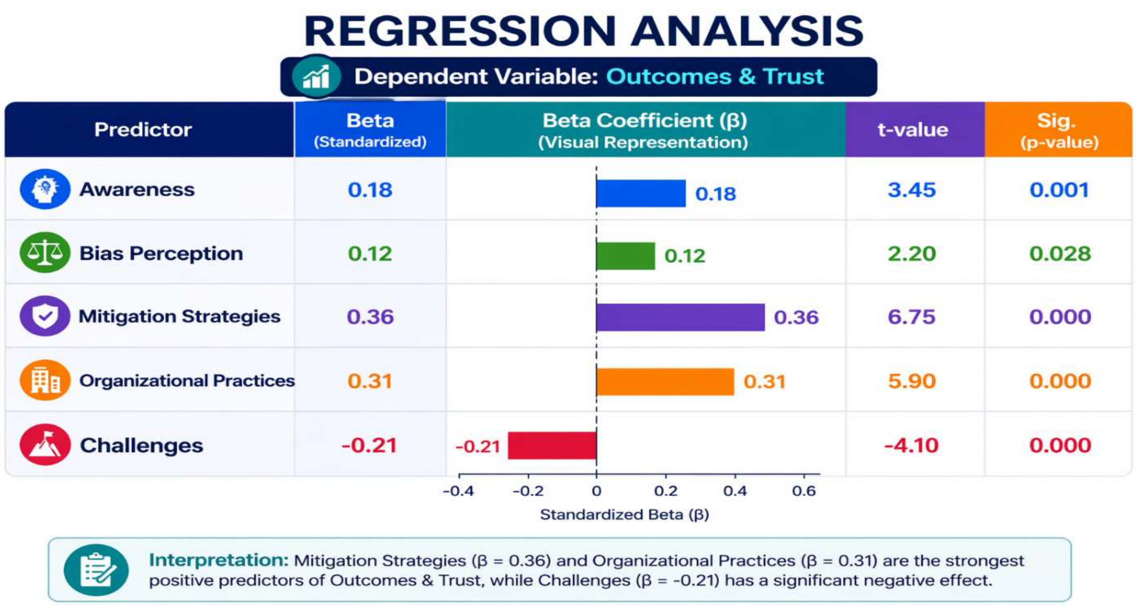
There is also a strong positive relationship between Trust and Organizational Practices (r = 0.68), indicating that organizational support contributes to development of trust. Conversely, Challenges demonstrate negative, significant correlations with every other variable, including Awareness (r = -0.30), Bias Perception (r = -0.25), Mitigation (r = -0.35), Organizational Practices (r = -0.40), and Trust (r = -0.38). It implies that, the more challenges are believed to be worse, the lesser positive perceptions and practices of AI.

The correlation analysis shows that there is a constant pattern: positive variables influence one another positively, challenges affect awareness and establishment of practices associated with AI adversely.

Figure 4

Regression Analysis



All the predictors have a significant effect on the dependent variable as indicated by the regression analysis ($p < 0.05$), indicating that it is necessary to explain the outcomes and trust variables. Among the predictors, the most significant positive effect is observed with "Mitigation Strategies" (β=0.36, t = 6.75, $p < 0.001$), and effective mitigation strategies are the most significant contributor to building trust and positive outcomes of AI.

The influence of the variable Organizational Practices is also significant (β=0.31, t = 5.90, $p < 0.001$) indicating that the institutional practices, policies and governance are instrumental in increasing trust. The perception that AI is aware of it is mediated with a medium positive influence (β = 0.18, t = 3.45, p = 0.001), which means that AI awareness has a positive impact on perceptions, although less than the institutional factors.

The positive effect of Awareness of Algorithmic Bias is lower (β =0.12, t = 2.20, p = 0.028), which means that awareness of bias has a weak correlation with a marginally larger trust, possibly due to increased vigilance and requests of responsibility.

Conversely, the negative influence of Challenges is also substantial (β=0.21, t = -4.10, p = 0.001) and implies that the perception of challenges and difficulties lowers trust and affects the outcomes negatively.

Collectively, the findings suggest that individual perception and awareness matter, whereas organisational support, and specifically, mitigation strategies, are the most critical triggers that contribute to trust in AI, with challenges posing a major negative determinant.

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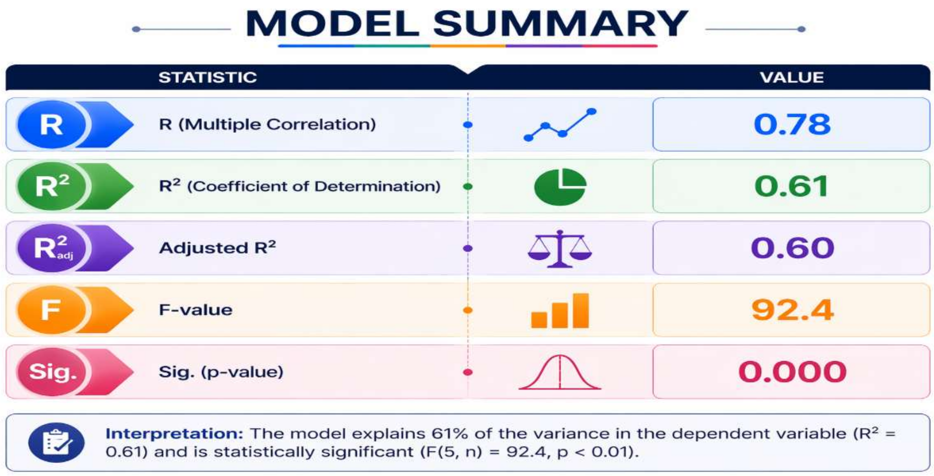
Figure 5
Model Summary

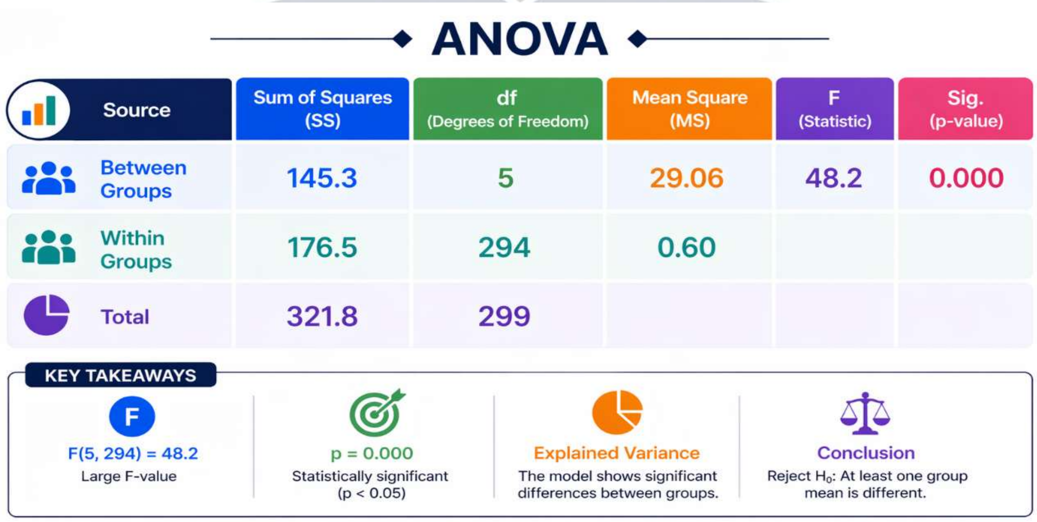

MODEL SUMMARY

STATISTIC		VALUE
R	R (Multiple Correlation)	0.78
R^2	R^2 (Coefficient of Determination)	0.61
R^2_{adj}	Adjusted R^2	0.60
F	F-value	92.4
Sig.	Sig. (p-value)	0.000

Interpretation: The model explains 61% of the variance in the dependent variable (R^2 = 0.61) and is statistically significant (F(5, n) = 92.4, p < 0.01).

The model summary indicates that the regression model fits well. The correlation coefficient (R = 0.78) indicates a strong correlation between the independent variables and the dependent variable (Outcomes & Trust). The coefficient of determination (R 2 = 0.61) means that the predictors explain 61 percent of variability in Outcomes and Trust which is very excellent in a social science research.
The adjusted R2 (0.60) compares with R 2, and this indicates that the model is not overfitted and the values included in the model are not arbitrarily produced by the inclusion of variables. This means that predictors are all significant.
Moreover, the F-statistic (F = 92.4, p < 0.001) shows that the regression model is statistically significant and the predictors as the group of variables explain the dependent variable significantly. Overall, the validity of the regression results is supported by the model being statistically significant, as well as possessing good explanatory power.

Figure 6
ANOVA


ANOVA

Source	Sum of Squares (SS)	df (Degrees of Freedom)	Mean Square (MS)	F (Statistic)	Sig. (p-value)
Between Groups	145.3	5	29.06	48.2	0.000
Within Groups	176.5	294	0.60		
Total	321.8	299			

KEY TAKEAWAYS

F(5, 294) = 48.2	p = 0.000	Explained Variance	Conclusion
Large F-value	Statistically significant (p < 0.05)	The model shows significant differences between groups.	Reject H_0: At least one group mean is different.

The ANOVA test reveals that there is a large difference between group means. The value of the sum of squares between groups (SS = 145.3, df = 5) compared with the value of the sum of squares within groups

(SS = 176.5, df = 294) provides a very large F-statistic ($F = 48.2$, $p < 0.001$), which means that at least one of the group means is significantly different.

The between groups mean square (MS = 29.06) indicates a large difference between the means of the groups compared to the within groups mean square (MS = 0.60), and this implies that it is not just a mere difference of randomness, but the significant differences.

Overall, the findings are strong group effects, which implies that the grouping variable has a significant impact on the answers. However, ANOVA does not show what groups differ, thus post hoc tests would have to be performed in order to find out which groups differ.

5. Discussion

The discussion of findings provides important suggestions on how to minimize the algorithmic bias in AI-based staffing. As indicated in the findings, all the constructs have high levels of internal consistency, which confirms the measurement model and builds confidence in the research findings. This result is consistent with other researchers who emphasized the importance of precise measurement tools when studying complex constructs such as algorithmic bias and AI adoption (Mujtaba and Mahapatra, 2024).

The important consequence is that the respondents were found to be highly aware of algorithmic bias. The descriptive statistics demonstrate that the respondents to the survey are not only familiar with AI technologies, but they are also very concerned with the possibility of biased decision-making. This result aligns with past studies that posit that awareness is a key factor in understanding and controlling bias in AI (Samala and Rawas, 2024). In addition, the positive correlation between awareness and mitigation strategies is strong and positive, which shows that practice of awareness professionals is more likely to support and implement fairness-enhancing strategies.

The strongest predictor of trust and outcomes in AI-driven hiring practices was mitigation strategies. Regression findings indicate that these strategies exert the most positive impact on trust, which implies that corporations that actively implement bias mitigation practices are more probable to establish trust among the stakeholders. This finding is consistent with prior studies emphasizing the role of open algorithm, varied information, and periodic audits in promoting fairness and responsibility (Albaroudi et al., 2024; Choain et al., 2023). It also defends the idea that technical solutions are the priority to enhance the credibility of AI technologies.

It was also discovered that organization practices had a strong role in influencing results. The positive correlation between organisational practices and trust indicates that organisational support, ethics and governance have a crucial role in facilitating the implementation of AI technologies. This follows the contention that AI integration is not only a technical but also an organizational and cultural issue (Harris, 2024). Organizations can mitigate bias and foster user trust by training and enforcing policies.

However, the study also indicates the adverse impact of adversities on each of the variables. The fact that the challenges have strong negative correlations with other constructs, including awareness, mitigation and trust, suggests that cost, expertise and lack of regulatory clarity may cause a serious impediment to implementation. This aligns with existing literature that indicates that these difficulties are obstacles to successful implementation of ethical AI (Ahmad, 2024; Islam, 2023). The fact that the responses to the challenges were relatively more variable also implies that they might not be universal across organisations and industries.

Altogether, the analysis reveals that despite comparatively high awareness and perception of bias, the effectiveness of AI hiring systems is highly dependent on the successful implementation of bias mitigation policies and organisational culture. However, simultaneously, we should discuss the existing challenges to make AI systems fair, clear, and reliable.

6. Conclusion

This paper has discussed the most pressing factors that affect the minimisation of the algorithmic bias in AI-based hiring systems, including perception, mitigation policies, awareness, and organisational practices and challenges. This research demonstrates that despite professionals being well-informed and well-educated regarding AI and the biases it may have, the implementation of formal strategies and organisational practices is essential to the success of bias mitigation strategies. It was demonstrated that mitigation of bias was the strongest predictor of trust and positive outcomes and must be pursued proactively with the incorporation of algorithm testing, broad spectrum of data sources and open decision-making.

Furthermore, they stated that institutional practices were viewed as a significant factor that predetermined the fairness and credibility of AI. An organisation that has established ethical principles, trained its staff and created a sense of responsibility will be better prepared to avoid bias and gain trust. However, despite these encouraging signs, the challenges such as technical constraints, implementation costs and regulatory uncertainties are there and impede the potential of unbiased AI.

In conclusion, this research suggests that in order to eliminate algorithmic bias, this is not only a technological issue but also a strategic and organisational one. Technical approaches and ethical management and governance are important in bringing them together. This multi-faceted nature of the problem may help firms to ensure that AI-based hiring is fair, unbiased and helpful to the decision-making process.

Recommendations

In terms of recommendations about the results of how to prevent AI recruiting algorithms from being biased, there are several things that could be considered. First, companies are going to need to work towards effective bias mitigation by regularly auditing algorithms, using diverse and representative data for training, and having transparent AI models. This will result in greater transparency of AI.

Second, they must improve governance by creating policies and ethics about the use of AI. AI Ethics Committees/Review Boards can be set up that will assist in tracking AI performance and fairness. In addition, HR and IT staff could be trained in the problem of bias and that it cannot be avoided through educating staff on AI literacy and ethics.

Third, it is recommended for organisations to adopt the human-in-the-loop approach to resolve the issue, which means AI should be combined with human feedback. This may help to remove the technology bias and human control in the loop. Lastly, to keep pace with the emerging demands and standards, it is recommended to collaborate with third-party specialists and authorities.

Finally, the barriers need to be removed by allocating resources, technological infrastructure and interdisciplinary mediation. The above recommendations will help companies gain trust, better recruitment decisions and ethical use of AI.

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