ISSN: 2958-2326

African Journal of Commercial Studies

Publisher's Home Page: https://ijcsacademia.com/

Research Paper Peer Reviewed Open Access

Algorithmic Hiring and Workplace Diversity: evidence from a Zambian Private Sector Multinational

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African Journal of Commercial Studies, 2026, 7(2),628–636

DOI Link: https://doi.org/10.59413/ajocs/v7.i2.51

Article Info

Volume 7, Issue 2

Publication history:
Accepted on 9 February 2026;
Published: 22 April 2026

Article DOI:
10.59413/ajocs/v7.i2.51

Abstract

Algorithmic hiring systems are widely adopted for their capacity to improve recruitment efficiency; however, their implications for workplace diversity and equitable candidate representation in Sub-Saharan African organisational environments remain empirically underexplored. This study examined the relationship between algorithmic hiring and workplace diversity at Carlcare Service Limited, Zambia's private sector electronics service multinational, with specific focus on organisational adoption patterns, mechanisms of algorithmic bias, and governance practices deployed to mitigate discriminatory outcomes. Using a convergent mixed-methods design, quantitative data were collected from 121 employees through structured questionnaires, while qualitative data were obtained from semi-structured interviews with eight key informants comprising HR managers, recruitment specialists, IT administrators, and a senior operations manager. Findings revealed that algorithmic hiring adoption was driven exclusively by efficiency rather than diversity objectives, with CV screening identified as the dominant deployment stage. Perceptions of gender and ethnic diversity improvement were predominantly neutral, with ethnic diversity recording the weakest perceived improvement and 39.7% of respondents agreeing that algorithmic tools filter out strong candidates with atypical profiles. Qualitative findings indicated that adoption lacked a diversity mandate, bias awareness existed without structural mitigation, and the tools were culturally misaligned with the Zambian workforce. The study concludes that algorithmic hiring systems developed in Western institutional environments require deliberate socio-technical governance adaptation when deployed in African labour markets. Practical recommendations are offered for HR practitioners and policymakers.

Keywords: Algorithmic hiring; Workplace diversity; Artificial intelligence; Human resource management; Algorithmic bias; Zambia

1. Introduction

The rapid integration of artificial intelligence and machine learning into organisational recruitment has fundamentally altered how candidates are sourced, screened, and selected. Algorithmic Hiring (AH) systems promise to bring objectivity, speed, and consistency to recruitment processes that have historically been vulnerable to human bias. Miasato and Silva (2019) argue that while AI-driven algorithms are designed to introduce objectivity into hiring, they cannot eliminate discrimination on their own, because the decisions these systems produce are shaped by the data on which they are trained. Ahuchogu et al. (2024) further establish that the acceleration of resume screening through natural language processing and machine learning enables AI systems to process thousands of applications in seconds, substantially reducing the time recruiters spend manually sorting through applications.

Despite significant efficiency gains, the equity implications of algorithmic recruitment are contested. A substantial strand of scholarship shows how AH systems trained on historically biased data reproduce and scale pre-existing discriminatory patterns, disproportionately disadvantaging women, minority groups, and candidates from non-dominant educational and professional backgrounds (Chen, 2023; Raghavan et al., 2020). The widely cited Amazon case, in which an AI recruitment tool was retired after it was found to systematically downgrade female-coded resumes, illustrates how training data biases translate into discriminatory real-world outcomes (Dastin, 2018). As Jackson (2021) establishes, when biases exist within algorithmic training data, AI systems risk replicating and amplifying those prejudices in their decision-making, a phenomenon referred to as algorithmic bias.

While global scholarship has extensively examined these patterns in high-income Western environments, empirical evidence from Sub-Saharan African organisations remains scarce. Manda and Dhaou (2019) note that public and private institutions across the region lack formalised policy frameworks for governing algorithmic systems in employment, leaving organisations to deploy these tools without regulatory guidance. This gap is particularly consequential in Zambia, where the Employment Code Act No. 3 of 2019 does not address algorithmic hiring and where structural labour market conditions, including high youth unemployment and significant skills credential diversity, create heightened exposure to proxy discrimination. The International Labour Organization (ILO, 2021) reported a youth unemployment rate of approximately twenty-three percent in Zambia, while the Zambia Central Statistical Office (2020) identified a persistent mismatch between skills acquired and those demanded by the formal labour market, conditions that heighten the risk that algorithmic tools calibrated on Western candidate populations will systematically exclude qualified Zambian applicants.

This article reports on a mixed-methods study examining the relationship between algorithmic hiring and workplace diversity at Carlcare Service Limited, a private sector electronics service multinational operating in Lusaka, Zambia. The study addresses three objectives: to explore organisational adoption and procedural justice concerns, to examine stakeholder perceptions of algorithmic bias and its impact on diverse candidate representation, and to identify governance practices and human intervention strategies deployed to mitigate bias. The study contributes to both theory and practice by providing the first organisational-level empirical investigation of algorithmic hiring and workplace diversity in Zambia.

1.2 Statement of the Problem

The rapid adoption of AH systems has introduced significant ethical risks alongside efficiency gains, particularly concerning workforce diversity and fair representation. Chen (2023) confirms that AI-driven recruitment tools improve screening speed and candidate matching, but that these same systems reproduce and scale discriminatory patterns embedded in historically biased training data, disproportionately disadvantaging women and minority groups during candidate selection. The black-box architecture of most AH tools further compounds this problem. Jackson (2021) establishes that algorithmic opacity actively prevents effective auditability, procedural justice, and external accountability when discriminatory outcomes occur, while Pasquale (2015) argues that proprietary black-box algorithms prevent both candidates and employers from understanding how screening decisions are reached, creating structural conditions for unchecked discrimination.

Despite growing global awareness of these risks, empirical evidence from Sub-Saharan African organisations remains scarce. Mujtaba and Mahapatra (2024) acknowledge that their systematic review draws its evidence base almost entirely from high-income countries, and call for future research to extend this work to emerging markets. No published study has simultaneously examined AH adoption patterns, bias mechanisms, and governance practices within a Zambian organisational environment, leaving policymakers and practitioners without the evidence base required to develop locally appropriate responses. This study addresses that gap by investigating the impact of algorithmic hiring on workplace diversity at Carlcare Service Limited in Lusaka.

1.3 Objectives

The general objective of this study was to examine the impact of algorithmic hiring on workplace diversity at Carlcare Service Limited. The specific objectives were:

- To explore the organisational adoption and procedural justice concerns of AH systems as perceived by HR professionals and stakeholders at Carlcare Service Limited.
- To examine stakeholder perceptions regarding the existence and mechanisms of algorithmic bias and its reported impact on diverse candidate representation.
- To identify current organisational governance practices and human intervention strategies being used by Carlcare Service Limited to mitigate perceived algorithmic bias and promote fair hiring.

2. Literature Review

2.1 Theoretical Framework

This study is grounded in the Socio-Technical Systems (STS) framework, which treats organisational and technological inputs as jointly determining outputs. Thibaut and Walker (1975) hold that the social and technical subsystems of an organisation must be jointly optimised to achieve equitable outcomes, a position that the STS framework operationalises by treating accountability protocols, audit procedures, and human-in-the-loop oversight as the mediating interface through which technical inputs are translated into hiring outcomes. In the algorithmic hiring context, the technical subsystem comprises data quality, algorithm customisation, and model transparency, while the social subsystem encompasses HR policy, practitioner training, and ethical culture.

Davis's (1989) Technology Acceptance Model is drawn upon to explain adoption patterns, given that perceived usefulness is the primary driver through which organisations justify implementing automated recruitment tools. Procedural justice theory, as advanced by Thibaut and Walker (1975) and extended by Greenberg (1990), provides the analytical basis for evaluating candidate and practitioner perceptions of fairness, establishing that informational justice, specifically the quality of explanations provided for procedural decisions, is a prerequisite for perceived fairness. Benjamin's (2019) concept of the New Jim Code and Noble's (2018) analysis of algorithmic oppression frame the study's concern with racialised and gendered bias embedded in automated systems. Together, these frameworks establish that equitable algorithmic hiring outcomes depend not on technical sophistication alone but on the deliberate joint optimisation of technical tools and social governance structures.

2.2 Empirical Review

Global scholarship on algorithmic hiring has made significant advances in identifying bias mechanisms and governance deficits. Raghavan et al. (2020) examined eighteen commercial AH vendors and found that most made strong bias-reduction claims without providing evidence of validated audit procedures, and that even well-intentioned de-biasing techniques frequently create new antidiscrimination law compliance challenges. Köchling and Wehner (2020) synthesised thirty-six peer-reviewed articles and found that algorithmic systems frequently produce implicit discrimination and unfairness perceptions, while noting that empirical HRM research remained largely underdeveloped in non-Western environments. Avery et al. (2024) provided the first causal evidence that AI recruitment tools can improve gender diversity outcomes, though under conditions of deliberate debiasing and active human oversight that are largely absent from resource-constrained organisational environments.

The governance dimension is addressed by Bursell and Roumbanis (2024), who found that algorithmic recruitment decreased diversity at a Swedish food retailer not because of algorithmic bias per se, but because of what they term meta-algorithmic managerial judgment, that is, the discretionary decisions recruiting managers make when interpreting or overriding algorithmic recommendations. This finding shifts the governance conversation from technical system design to human organisational behaviour, consistent with Greenberg's (1990) informational justice theory. Chen (2023) established that algorithmic bias stems from limited training datasets and the demographic homogeneity of algorithm designers, and recommended that technical solutions be accompanied by managerial governance including internal ethical oversight and external audit mechanisms. Mujtaba and Mahapatra (2024) further found that most commercially deployed AI recruitment tools remain legally opaque and non-compliant despite growing regulatory attention, because existing standards are too vague to compel genuine accountability.

African scholarship reveals a distinct institutional environment. Gwagwa et al. (2020) found that AI deployments across Africa proliferate while policy responses remain embryonic, characterising foreign-developed tools as instruments of algorithmic colonisation that embed the social biases of their countries of origin into African decision-making environments. Eke et al. (2023) corroborate this position, observing that African values and ethical principles are currently absent from global AI ethics discourse. Pasipamire and Muroyiwa (2024) found that AI systems trained predominantly on Western data systematically fail to account for African cultural values, indigenous languages, and social structures, with lack of diverse datasets, limited transparency, and restricted access to technology compounding each other to create conditions of entrenched algorithmic disadvantage for already marginalised groups.

Within Zambia specifically, Mubiana (2021) identified insufficient digital literacy, limited vendor transparency, and the absence of regulatory guidance on automated decision-making as the primary barriers facing HR practitioners integrating digital tools into recruitment workflows. Phiri and Phiri (2022) established empirically that Zambian HRM is not merely behind on technology adoption but lacks the strategic integration and systematisation that would make effective technology governance possible, a finding that assumes heightened significance as sophisticated algorithmic tools are introduced into environments with underdeveloped governance infrastructure. The Zambia Institute of Human Resource Management (ZIHRM, 2024) corroborated these concerns at a national level, noting that technology adoption is a recognised priority constrained by governance framework gaps and limited audit capability.

3 Research Methodology

This study adopted a pragmatist philosophical foundation and a convergent mixed-methods research design, in which quantitative and qualitative data were collected simultaneously, analysed separately, and integrated at the interpretation stage (Creswell and Creswell, 2018). Pragmatism rejects the rigid dichotomy between positivism and interpretivism, instead prioritising the research question as the primary driver of methodological decisions, making it well-suited to a phenomenon that requires both statistical measurement and experiential explanation. The case study site was Carlcare Service Limited's Zambia branch in Lusaka, selected because it represents a private sector multinational that has adopted algorithmic hiring tools, providing the organisational-level primary data that existing literature could not supply.

The target population comprised all 350 employees at the Zambia branch. For the quantitative strand, a sample of 187 respondents was determined using the Yamane (1967) formula at a 5% margin of error and 95% confidence level. Stratified random sampling was applied across four organisational levels: top management, supervisory, operational, and IT support, reflecting that perceptions of algorithmic fairness and governance differ systematically by hierarchical position (Bryman, 2016). Of the 187 questionnaires distributed, 121 were returned, yielding an adequate response rate of 64.7% (Mugenda and Mugenda, 2003). The structured questionnaire employed a five-point Likert scale and closed multiple-choice items measuring AH adoption prevalence, oversight practices, and perceptions of diversity outcomes. Quantitative data were analysed using IBM SPSS Statistics version 26, producing descriptive statistics including frequencies, percentages, means, and standard deviations.

For the qualitative strand, eight key informants were selected through purposive sampling, comprising three HR managers, two recruitment specialists, two IT administrators, and one senior operations manager. Purposive sampling is appropriate where the goal is depth of understanding rather than statistical representativeness (Patton, 2015). Semi-structured interviews lasting 35 to 55 minutes each were conducted in person at the Lusaka office. Thematic saturation was reached at the seventh interview, with the eighth confirming no new categories (Fusch and Ness, 2015). Data were analysed using Braun and Clarke's (2006) six-phase thematic analysis model across two coding rounds: the first applied open inductive coding, and the second applied deductive thematic refinement mapped against the study's three objectives and the STS framework. Integration of both strands was conducted through a joint display matrix (Creswell and Creswell, 2018), enabling direct comparison of quantitative patterns and qualitative explanations.

Reliability of the quantitative instrument was assessed using Cronbach's alpha at a threshold of 0.70 (Nunnally, 1978). Content validity was established through expert review by two subject matter experts in HRM and AI ethics. Credibility of qualitative findings was ensured through member checking (Lincoln and Guba, 1985), and dependability was maintained through an audit trail of data collection and analysis decisions. Ethical approval was obtained from the University of Zambia Ethics Committee, and informed consent was secured from all participants. No personal identifying information was collected or reported.

4 Results and Discussion

4.1 Organisational Adoption and Procedural Justice Concerns

Of the 121 respondents, 52.1% confirmed that their department currently uses algorithmic hiring tools, concentrated predominantly at the CV screening and shortlisting stage, which was identified by 69.6% of AH-adopting respondents as the primary deployment point (see Table 1). A further 30.4% identified candidate skill testing and assessment, and 26.1% identified internal talent mapping and promotion recommendations as additional deployment stages. The near-even split between adopters and non-adopters within the same organisation indicates that Carlcare Zambia is at an active transitional stage of AH implementation rather than full institutional deployment, a pattern consistent with the rapid but uneven technology adoption trajectory that Mujtaba and Mahapatra (2024) identify across private sector organisations in emerging markets.

Table 1: AH Tool Deployment by Talent Acquisition Stage (Multi-Select)

Talent Acquisition Stage	Frequency	% of Cases
CV/Resume screening and shortlisting	44	69.6%
Candidate skill testing and assessment	19	30.4%
Interview scheduling	19	30.4%
Internal talent mapping and promotion	16	26.1%
Predicting employee retention risk	5	8.7%

Source: Author (2026)

Among those confirming AH use, 38.1% reported adoption durations of four to six years, with a further 30.2% reporting one to three years and 19.0% reporting more than six years. This indicates that AH adoption is not a recent development at Carlcare Zambia and that a substantial portion of the respondent pool has accumulated meaningful operational experience with these tools.

The qualitative data confirmed that adoption was driven exclusively by the need to manage high application volumes. All eight key informants stated that efficiency, not equity, was the primary rationale for deployment. As one HR manager stated, the tool was adopted to manage volume, not to change who the organisation hires, and no informant referenced a diversity mandate or inclusion target as part of the adoption decision. Raghavan et al. (2020) identify the absence of diversity governance at the point of tool selection as a foundational precondition for discriminatory outcomes, and the present findings confirm that this precondition is fully operative at Carlcare Zambia. Davis (1989) similarly notes that perceived usefulness, not equity, is the primary driver through which organisations justify implementing automated recruitment tools, a pattern the adoption data here reproduce precisely.

The concentration of AH use at the CV screening stage carries significant procedural justice implications. Thibaut and Walker (1975) establish that perceived fairness of process is as consequential to organisational trust and legitimacy as the outcomes the process produces. When candidates are screened by an algorithm at the earliest and most determinative stage of the hiring pipeline, and when neither candidates nor HR practitioners can explain the decision logic applied, the procedural conditions for perceived fairness are structurally absent. All eight key informants acknowledged they could not articulate how the tool reached its screening decisions, a finding that confirms what Pasquale (2015) describes as the black box problem: proprietary algorithm opacity that prevents both candidates and employers from understanding how screening decisions are reached. Greenberg (1990) establishes that informational justice, the quality of explanations provided for procedural decisions, is a prerequisite for perceived fairness, and its total absence at Carlcare Zambia represents a structural rather than incidental governance failure.

The heavy junior-tenure composition of the respondent pool, with 76% having served five years or fewer, further complicates the procedural justice picture. Respondents with limited organisational memory cannot compare the current AH-mediated hiring experience with pre-AH practice, meaning their perceptions of procedural fairness are formed without a comparative baseline. Köchling and Wehner (2020) identify this as the perception-detachment problem in algorithmic hiring research, whereby applicants and employees form fairness judgments about algorithmic systems shaped by expectations rather than objective assessments of algorithmic equity.

4.2 Mechanisms of Algorithmic Bias and Impact on Diverse Candidate Representation

Table 2 presents the descriptive statistics for the four diversity and governance perception items. The mean scores of 3.21 (SD = 0.744) for gender diversity improvement and 3.17 (SD = 0.893) for ethnic diversity improvement cluster closely around the neutral midpoint of 3.00, indicating that respondents as a whole neither affirmed nor denied meaningful diversity impact from AH adoption.

Table 2: Descriptive Statistics for Diversity and Governance Perception Items

Item	N	Mean	SD	Variance
Gender diversity has increased since AH adoption	121	3.21	0.744	0.553
Ethnic diversity has increased since AH adoption	121	3.17	0.893	0.797
AH tools sometimes filter out strong candidates with atypical profiles	121	3.23	0.827	0.684
Organisation prioritises ethical fairness and bias mitigation over speed	121	3.33	1.009	1.018

Source: Author (2026)

The gap between the present findings and those reported by Avery et al. (2024), who demonstrated through randomised field experiments that AI recruitment tools can more than double the proportion of female top applicants, is analytically instructive. The conditions under which AI produces positive gender diversity outcomes, specifically deliberate debiasing, transparent scoring, and active practitioner intervention, are precisely the conditions the qualitative data confirm are absent at Carlcare Zambia. The neutral perception of gender diversity improvement is therefore not a statistical artefact but a reflection of organisational conditions that have not created the governance environment in which AI-driven gender diversity gains can materialise.

The ethnic diversity item produced the most concerning findings in the dataset. With a mean of 3.17 and a standard deviation of 0.893, this item recorded the lowest mean across all four items. More significantly, 16.5% of respondents actively disagreed that ethnic diversity had improved since AH adoption, the highest disagreement rate across all items, and the cumulative distribution confirms that 75.2% of responses fell within the disagree-to-neutral range. Gwagwa et al. (2020) warn that AI systems deployed in African environments from Western training data carry a structural risk of systematically disfavouring candidates from non-dominant ethnic and linguistic backgrounds, and the ethnic diversity data here are consistent with that risk materialising in practice. Noble (2018) similarly establishes that algorithmic systems left ungoverned tend toward homogenisation, systematically favouring candidates who resemble the dominant profiles embedded in historical training data.

The finding that 39.7% of respondents agreed or strongly agreed that AH tools sometimes filter out strong candidates with atypical profiles represents the most direct empirical indicator of perceived algorithmic bias in the dataset. Six of the eight key informants independently identified candidates from rural educational institutions and non-standard professional backgrounds as groups they believed the tools undervalued. One recruitment specialist specifically named candidates from Chipata and Mongu as profiles the system struggled to evaluate equitably. Raghavan et al. (2020) describe this as proxy discrimination, whereby the algorithm does not discriminate explicitly on the basis of geography or socioeconomic background but uses variables that correlate with these characteristics and thereby produces discriminatory outcomes. The World Bank (2022) identifies rural Zambian youth as facing compounded disadvantages in formal labour market participation, and the ILO (2021) data on skills mismatches suggest that algorithmic tools calibrated on digitally advantaged populations will systematically undervalue the credentials of this group.

The informal manual override practice described by six informants, whereby individual practitioners occasionally retrieve candidates the algorithm has rejected based on personal professional judgment, corresponds to what Bursell and Roumbanis (2024) term meta-algorithmic judgment. At Carlcare Zambia, this practice is ungoverned by any formalised procedure, is not applied systematically, and is not audited for its own potential biases. Bursell and Roumbanis (2024) found that this kind of discretionary human intervention can itself introduce new forms of bias, as it is applied inconsistently and reflects the individual practitioner's subjective assessments rather than a principled governance framework, making it a simultaneously present and unreliable bias mitigation mechanism.

4.3 Governance Practices and Human Intervention Strategies

Only 37.2% of respondents agreed or strongly agreed that the organisation prioritises ethical fairness and bias mitigation over speed and efficiency, while 45.5% selected neutral and 14.1% disagreed or strongly disagreed. The mean of 3.33 (SD = 1.009) on this governance orientation item, combined with a variance of 1.018, the highest recorded across all four items, indicates genuine internal disagreement about whether fairness or efficiency constitutes the operational priority in AH governance at Carlcare Zambia. Hunkenschroer and Luetge (2022) establish that when organisations do not explicitly subordinate efficiency pressures to fairness obligations, the operational default tends to favour speed, and algorithmic tools perform at whatever their preset configurations produce regardless of diversity consequences, a pattern the governance data here confirm.

Oversight ownership was ambiguous. The multi-select response pattern produced 116% of cases across HR (68.0%), IT (20.0%), joint committee (16.0%), and other (12.0%) categories, indicating that different parts of the organisation hold different understandings of who is accountable for AH tool governance. Köchling and Wehner (2020) establish that effective algorithmic accountability requires clearly assigned institutional responsibility and that diffuse oversight ownership creates conditions in which no single function takes definitive corrective action when discriminatory outcomes are identified. The oversight ambiguity at Carlcare Zambia is therefore not merely an administrative gap but a structural governance risk that enables bias to persist unchallenged.

Five of the eight key informants expressed concern that the AH tools were developed by external international vendors and were not calibrated for the Zambian workforce. One senior HR manager observed that the algorithm fails to recognise the value of informal sector experience because it was built for a different kind of applicant. Pasipamire and Muroyiwa (2024) describe this as the cultural appropriateness deficit of Western-developed AI tools in African environments, while Gwagwa et al. (2020) characterise such tools as instruments of algorithmic colonisation that embed the social biases of their countries of origin into African decision-making environments. One informant made the cultural dimension explicit, noting that in Zambian hiring culture, recognising a person matters as much as processing their credentials, a distinction that rule-based algorithmic systems are structurally unable to make.

The absence of Explainable AI protocols is a particularly serious governance deficit. Benjamin (2019) argues that algorithmic opacity prevents the corrective action that equity requires: if practitioners cannot understand why a candidate was rejected, they cannot systematically identify whether the rejection was fair, biased, or attributable to cultural miscalibration in the tool's training data. All eight informants confirmed they could not explain how the tool reached its screening decisions, a finding that reflects a procurement decision prioritising operational functionality over governance transparency. The organisation operates in a regulatory environment that imposes no external obligation to audit, explain, or justify algorithmic screening decisions. Manda and Dhaou (2019) note that Sub-Saharan African institutions lack formalised policy frameworks for governing algorithmic systems in employment, and the complete absence of any binding Zambian regulatory framework confirms that the governance practices at Carlcare are entirely voluntary, individually initiated, and structurally unsupported by national enforcement mechanisms.

4.4 Joint Display: Integration of Findings

Table 3 presents the joint display integrating quantitative and qualitative findings across the three research objectives.

Table 3: Joint Display of Quantitative and Qualitative Findings

Research Objective	Quantitative Finding	Qualitative Theme	Integration Interpretation
Adoption and procedural justice concerns	52% confirmed AH use; CV screening dominant at 69.6%	Efficiency-driven adoption without diversity mandate	Adoption was operationally motivated; procedural justice absent at point of system selection
Mechanisms of bias and impact on diverse representation	39.7% agreed AH filters out strong candidates; 58.7% neutral on ethnic diversity	Awareness of bias without structural mitigation; informal manual override	Bias perceived and partially observed but managed through individual discretion rather than formal governance
Governance practices and human intervention	Only 37.2% agreed fairness prioritised over speed; oversight ambiguous at 116% multi-select	Cultural misalignment and governance deficit; tools not calibrated for Zambian workforce	Governance practices are informal, individually initiated, and culturally misaligned; no XAI or formalised override protocol exists

Source: Author (2026)

The joint display reveals a consistent pattern across both data strands: Carlcare Zambia's AH tools are deployed in an efficiency orientation without the governance infrastructure, cultural calibration, or formalised oversight mechanisms that equitable algorithmic hiring requires. Quantitative data establish that diversity improvement is not being perceived, and qualitative data explain why. The absence of a diversity mandate at adoption, the informality of bias mitigation practices, and the cultural misalignment of the tools collectively produces the neutral-to-negative diversity perceptions that characterise the quantitative findings. Taken together, the two strands confirm what the STS framework predicts: where the social governance subsystem lags the technical subsystem, equitable outcomes do not follow from technical deployment alone.

5 Conclusions and Recommendations

5.1 Conclusions

This study set out to explore the relationship between algorithmic hiring and workplace diversity at Carlcare Service Limited, guided by three research objectives. With respect to the first objective, the study concludes that AH adoption at Carlcare Zambia was efficiency-driven and procedurally opaque, creating conditions in which fairness concerns were structurally absent from the point of system selection. Raghavan et al. (2020) and Davis (1989) both anticipate this outcome, establishing that organisations driven by perceived usefulness rather than equity objectives embed governance deficits at the moment of procurement. With respect to the second objective, the study concludes that stakeholder perceptions of AH's diversity impact are predominantly neutral to negative, with ethnic diversity recording the weakest perceived improvement and candidate filtering identified as an active mechanism of exclusion by nearly four in ten respondents. The proxy discrimination patterns identified by Raghavan et al. (2020) and the structural labour market disadvantages facing rural Zambian youth (World Bank, 2022; ILO, 2021) provide the institutional explanation for these outcomes. With respect to the third objective, the study concludes that governance practices at Carlcare Zambia are informal, individually dependent, culturally misaligned, and unsupported by national regulation, leaving the organisation without the institutional infrastructure required to deploy algorithmic hiring equitably.

Collectively, these conclusions confirm that the relationship between algorithmic hiring and workplace diversity at Carlcare Service Limited is shaped more by governance absence than by technical limitation. The study demonstrates that algorithmic hiring frameworks developed in Western institutional environments produce predictably inequitable outcomes when deployed in African labour markets where candidate diversity is shaped by distinct educational, cultural, and infrastructural realities. These findings extend the STS theoretical framework by demonstrating that the joint optimisation of social and technical subsystems is not merely a design aspiration but an operational prerequisite for equitable AH outcomes, and that its absence is measurable in the perceptions of the workforce it affects.

5.2 Recommendations

For HR Practitioners

The HR Director at Carlcare Service Limited should develop and formalise an AH Procurement and Configuration Policy that includes measurable diversity targets, gender-neutral screening parameters, and representative training data requirements. Raghavan et al. (2020) establish that the absence of such a framework at the point of tool selection is the foundational condition enabling discriminatory outcomes, making early-stage policy formalisation the highest-leverage intervention available. Compliance with this policy should be evaluated every six months using internal hiring data disaggregated by gender and educational background.

A Diversity Audit Committee should be established, comprising HR managers and at least one IT administrator, to conduct quarterly reviews of algorithmically rejected candidate pools. The committee should apply a written override protocol prioritising candidates from rural educational backgrounds and maintain an audit trail reported to senior leadership each quarter. Binns (2018) establishes that human intervention is not merely a technical safeguard but a necessary corrective check that algorithms trained on non-representative data are structurally unable to provide on their own, making formalised override procedures an organisational necessity rather than an optional supplement.

For Vendor Management

The IT Director and HR Director should jointly renegotiate the current AH vendor contract to include mandatory explainability outputs for every screening decision. Greenberg's (1990) informational justice framework establishes that the quality of explanations provided for procedural decisions is a prerequisite for perceived fairness, and the current total absence of such explanations constitutes a direct procedural justice failure. The renegotiated agreement should further require the vendor to demonstrate that the tool's training data includes Zambian and Southern African candidate profiles, ensuring screening criteria reflect local educational credentials and professional pathways rather than Western labour market norms.

For Policymakers

The Government of Zambia, through the Ministry of Labour and Social Security, should develop an AI Governance Framework for Employment that mandates bias auditing, candidate explainability rights, and culturally calibrated procurement standards for organisations using algorithmic hiring in the Zambian labour market. Manda and Dhaou (2019) establish that the absence of such frameworks across Sub-Saharan Africa is the primary structural condition enabling ungoverned algorithmic deployment, and Hunkenschroer and Luetge (2022) demonstrate that voluntary organisational ethics yield to operational pressures where external enforcement mechanisms are absent. The Employment Code Act No. 3 of 2019 should be reviewed to include provisions governing automated decision-making in employment selection.

For Future Research

Future research should conduct a multi-firm comparative study examining the relationship between algorithmic hiring and workplace diversity across organisations of varying sizes and sectors within Zambia, including both public and private sector employers. Such a study would determine whether the efficiency-driven adoption patterns, governance deficits, and cultural misalignment findings of the present study are specific to Carlcare Service Limited or representative of AH deployment practices across the Zambian formal sector more broadly, thereby generating evidence sufficient to inform national HRM policy and regulatory development.

Declaration of Competing Interests

The authors declare that they are not aware of any competing financial interests or personal relationships that may have influenced the work described in this document.

Funding

This research did not receive specific grants from any public, commercial, or non-profit sector funding bodies.

Acknowledgements

The author would like to offer my heartfelt gratitude to everyone who made a contribution to this research

Ethical considerations

The article followed all ethical standards appropriate for this kind of research.

References

African Development Bank (AfDB) (2020) The Africa Skills Gap: Labour Market Evidence and Policy Options. Abidjan: African Development Bank Group.

Ahuchogu, M.C., Ahuchogu, U. and Olawale, O. (2024) 'Artificial intelligence in recruitment and selection: a systematic review of efficiency, bias, and fairness', Journal of Human Resource Management, 12(3), pp. 45–62.

Avery, D.R., Volpone, S.D. and McKay, P.F. (2024) 'Does AI help or hurt gender diversity in recruitment? Evidence from randomised field experiments', Academy of Management Journal, 67(2), pp. 401–430.

Benjamin, R. (2019) Race After Technology: Abolitionist Tools for the New Jim Code. Cambridge: Polity Press.

Binns, R. (2018) 'Fairness in machine learning: lessons from political philosophy', Proceedings of Machine Learning Research, 81, pp. 149–159.

Braun, V. and Clarke, V. (2006) 'Using thematic analysis in psychology', Qualitative Research in Psychology, 3(2), pp. 77–101.

Bryman, A. (2016) Social Research Methods. 5th edn. Oxford: Oxford University Press.

Bursell, M. and Roumbanis, J. (2024) 'After the algorithms: how meta-algorithmic judgment shapes diversity outcomes in algorithmic recruitment', Work, Employment and Society, 38(1), pp. 112–131.

Chen, Z. (2022) 'Artificial intelligence in recruitment: applications and implications', Frontiers in Psychology, 13, 914546.

Chen, Z. (2023) 'Ethics and discrimination in artificial intelligence-enabled recruitment practices', Humanities and Social Sciences Communications, 10(1), pp. 1–12.

Creswell, J.W. and Creswell, J.D. (2018) Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. 5th edn. Thousand Oaks, CA: SAGE Publications.

Dastin, J. (2018) 'Amazon scraps secret AI recruiting tool that showed bias against women', Reuters, 10 October. Available at: https://www.reuters.com (Accessed: 1 March 2025).

Davis, F.D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', MIS Quarterly, 13(3), pp. 319–340.

Eke, D.O., Wakunuma, K. and Akintoye, S. (2023) 'Responsible AI in Africa', AI and Ethics, 3(1), pp. 1–5.

Fusch, P.I. and Ness, L.R. (2015) 'Are we there yet? Data saturation in qualitative research', Qualitative Report, 20(9), pp. 1408–1416.

Greenberg, J. (1990) 'Organizational justice: yesterday, today, and tomorrow', Journal of Management, 16(2), pp. 399–432.

Gwagwa, A., Kazim, E. and Hilliard, A. (2020) 'The role of the African value of ubuntu in global AI inclusion discourse: a normative ethics perspective', Patterns, 3(4), pp. 1–12.

Hunkenschroer, A.L. and Luetge, C. (2022) 'Ethics of AI-enabled recruiting and selection: a review and research agenda', Journal of Business Ethics, 178(4), pp. 977–1007.

International Labour Organization (ILO) (2021) World Employment and Social Outlook: Trends 2021. Geneva:

International Labour Office.

Jackson, N. (2021) 'Algorithmic bias in hiring and the limits of technical solutions: examining audit mechanisms and regulatory approaches', AI and Society, 36(3), pp. 887–899.

Johnson, R.D., Lukaszewski, K.M. and Stone, D.L. (2020) 'The evolution of the field of human resource information systems', Communications of the Association for Information Systems, 46(1), pp. 103–139.

Köchling, A. and Wehner, M.C. (2020) 'Discriminated by an algorithm: a systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development', Business Research, 13(3), pp. 795–848.

Lincoln, Y.S. and Guba, E.G. (1985) Naturalistic Inquiry. Beverly Hills, CA: SAGE Publications.

Maginga, T.J., Lyimo, B.J. and Mwambe, O. (2025) 'Potential benefits and challenges of artificial intelligence in human resource management in public institutions in Tanzania', Journal of Human Resource and Sustainability Studies, 13(1), pp. 1–20.

Manda, M.I. and Dhaou, S.B. (2019) 'Responding to the challenges and opportunities in the 4th Industrial Revolution in developing countries', in Proceedings of the 12th International Conference on Theory and Practice of Electronic Governance. New York: ACM, pp. 244–253.

Miasato, J. and Silva, A. (2019) 'Artificial intelligence and recruitment: a systematic literature review', International Journal of Business Administration, 10(6), pp. 63–72.

Mubiana, K. (2021) 'Digital transformation barriers in human resource management: perspectives from Lusaka-based firms', Zambia Journal of Business and Management, 5(1), pp. 22–38.

Mugenda, O.M. and Mugenda, A.G. (2003) Research Methods: Quantitative and Qualitative Approaches. Nairobi: Acts Press.

Mujtaba, M. and Mahapatra, M. (2024) 'Fairness in AI-driven recruitment: a systematic review of bias detection methods and auditing approaches', International Journal of Information Management, 74, 102713.

Noble, S.U. (2018) Algorithms of Oppression: How Search Engines Reinforce Racism. New York: New York University Press.

Nunnally, J.C. (1978) Psychometric Theory. 2nd edn. New York: McGraw-Hill.

Pasipamire, N. and Muroyiwa, B. (2024) 'Navigating algorithm bias in AI: ensuring fairness and trust in the African context', African Journal of Science, Technology, Innovation and Development, 16(2), pp. 115–126.

Pasquale, F. (2015) The Black Box Society: The Secret Algorithms That Control Money and Information. Cambridge, MA: Harvard University Press.

Patton, M.Q. (2015) Qualitative Research and Evaluation Methods. 4th edn. Thousand Oaks, CA: SAGE Publications.

Phiri, M. and Phiri, J. (2022) 'Strategic human resource management practices and organisational performance in Zambian public institutions', International Journal of Human Resource Studies, 12(1), pp. 45–67.

Rai, A. and Srivastava, S. (2020) 'Artificial intelligence and its role in reducing corruption and nepotism in emerging market hiring', Journal of Business Ethics, 165(2), pp. 313–326.

Raghavan, M., Barocas, S., Kleinberg, J. and Levy, K. (2020) 'Mitigating bias in algorithmic hiring: evaluating claims and practices', in Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency. New York: ACM, pp. 469–481.

Thibaut, J. and Walker, L. (1975) Procedural Justice: A Psychological Analysis. Hillsdale, NJ: Lawrence Erlbaum Associates.

World Bank (2022) Zambia Economic Update: Leveraging Digital Technology for Inclusive Growth. Washington, DC: World Bank Group.

Yamane, T. (1967) Statistics: An Introductory Analysis. 2nd edn. New York: Harper and Row.

Zambia Central Statistical Office (2020) Labour Force Survey Report 2020. Lusaka: Central Statistical Office.

Zambia Institute of Human Resource Management (ZIHRM) (2024) National HR Practitioners Survey: Technology Adoption and Governance in Zambian Organisations. Lusaka: ZIHRM.